

MASTERARBEIT | MASTER'S THESIS

Titel | Title

Extended Integrated Procurement Allocation, Production
Planning, and Routing Problem for Perishable Food Supply
Chains

verfasst von | submitted by
Naranzul Amartugs

angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of
Master of Science (MSc)

Wien | Vienna, 2026

Studienkennzahl lt. Studienblatt | Degree
programme code as it appears on the
student record sheet:

UA 066 915

Studienrichtung lt. Studienblatt | Degree
programme as it appears on the student
record sheet:

Masterstudium Betriebswirtschaft

Betreut von | Supervisor:

Univ.-Prof. Dr. Jan Fabian Ehmke

Mitbetreut von | Co-Supervisor:

Peiman Ghasemi PhD

Zusammenfassung

Perishable Food Supply Chains (PFSCs) erfordern eine enge Koordination von Beschaffung, Produktion, Lagerung und Distribution, da verderbliche Produkte nur eine begrenzte Haltbarkeit aufweisen und unter kontrollierten Bedingungen gelagert und transportiert werden müssen. Ineffizienzen in diesen Prozessen können zu erhöhten Lebensmittelverlusten, höheren Betriebskosten und zusätzlichen Umweltbelastungen führen. Besonders kleine und mittlere Unternehmen (KMU) sind von diesen Herausforderungen betroffen. Bestehende Modelle zur Beschaffungsplanung, Produktionsplanung und Tourenplanung betrachten diese Entscheidungen häufig getrennt voneinander, beruhen auf vereinfachenden Annahmen oder berücksichtigen Unsicherheiten und Verderblichkeitsprozesse nur unzureichend.

Diese Arbeit entwickelt ein **Extended Integrated Procurement Allocation, Production Planning, and Routing Problem (EIPAPRP)**, das Beschaffungs-, Produktions-, Lagerungs- und Distributionsentscheidungen in einem integrierten Optimierungsrahmen verbindet. Aufbauend auf dem Modell von (Hashemi-Amiri et al., 2023) erweitert die vorgeschlagene Modellierung den bestehenden Ansatz um drei wesentliche Aspekte: (i) die explizite Berücksichtigung von Fertigwaren-Kühlagerung, (ii) die Abbildung von Mehrkomponenten-Produktion durch Stücklisten sowie (iii) die Einbeziehung transportbedingter CO₂-Emissionen als Nachhaltigkeitskomponente. Zur Berücksichtigung von Unsicherheiten in Angebot und Nachfrage wird Distributionally Robust Optimization (DRO) eingesetzt. Dadurch können Entscheidungen entwickelt werden, die auch unter unterschiedlichen plausiblen Datenverteilungen robust bleiben.

Das Modell wird anhand einer realen Fallstudie eines mittelständischen Herstellers von verzehrfertigen Lebensmitteln in der Mongolei untersucht. Historische Betriebsdaten dienen zur Bewertung der Umsetzbarkeit und praktischen Anwendbarkeit des Ansatzes. Die durchgeführten Experimente analysieren Beschaffungs-, Produktions-, Lagerungs- und Distributionsentscheidungen unter verschiedenen Unsicherheitsszenarien und bewerten deren Auswirkungen auf Kosten und Umweltleistung.

Die Ergebnisse zeigen, dass integrierte Planung die Koordination zwischen den einzelnen Bereichen der Lieferkette verbessern und die Widerstandsfähigkeit gegenüber Unsicherheiten erhöhen kann. Darüber hinaus verdeutlichen die Ergebnisse, wie wirtschaftliche und ökologische Zielsetzungen innerhalb eines gemeinsamen Entscheidungsunterstützungsrahmens für PFSCs ausgewogen berücksichtigt werden können.

Abstract

Perishable food supply chains (PFSCs) require close coordination of procurement, production, storage, and distribution activities due to the limited shelf life of products and the strict conditions required to maintain quality. Inefficiencies in these processes can increase food waste, operational costs, and environmental impact, particularly for small- and medium-sized enterprises (SMEs). Existing studies on supplier selection, production scheduling, and vehicle routing often address these decisions separately, rely on restrictive assumptions, or do not fully account for uncertainty and perishability.

This thesis develops an **Extended Integrated Procurement Allocation, Production Planning, and Routing Problem (EIPAPRP)** model that integrates procurement, production, cold-storage operations, and distribution decisions within a single optimization framework. Building on the model proposed by (Hashemi-Amiri et al., 2023), the proposed framework introduces three main extensions: (i) explicit modeling of finished-goods cold-storage, (ii) multi-ingredient production through Bills of Materials (BOM), and (iii) transportation-related CO₂ emissions as an environmental sustainability component. To address uncertainty in supply and demand, the model incorporates **Distributionally Robust Optimization (DRO)**, allowing decisions to remain feasible under a range of plausible demand and supply conditions.

The proposed framework is evaluated using a case study of a mid-sized ready-to-eat meal manufacturer in Mongolia. Historical operational data are used to evaluate the model's feasibility and applicability under real operating conditions. Computational experiments examine procurement, production, inventory, and routing decisions under different uncertainty scenarios and assess their impact on cost and environmental performance.

The findings indicate that integrated planning can improve coordination across supply chain activities and support more resilient decision-making under uncertainty. In addition, the results illustrate how economic and environmental objectives can be balanced within a unified decision-support framework for perishable food supply chains.

Table of Contents

ZUSAMMENFASSUNG	I
ABSTRACT	II
TABLE OF CONTENTS.....	III
LIST OF TABLES	V
LIST OF FIGURES.....	VII
LIST OF ABBREVIATIONS	VIII
1. INTRODUCTION.....	1
1.1 BACKGROUND	1
1.2 PROBLEM CONTEXT AND MOTIVATION.....	1
1.3 RESEARCH QUESTION AND OBJECTIVES	2
1.4 THESIS STRUCTURE	3
2. LITERATURE REVIEW.....	3
2.1 INTRODUCTION TO THE LITERATURE REVIEW.....	3
2.2 FOUNDATIONS OF PERISHABLE FOOD SUPPLY CHAINS	4
2.2.1 <i>Perishability and Core Characteristics of PFSCs</i>	4
2.3 SUPPLIER SELECTION AND ORDER ALLOCATION IN PFSCS	7
2.3.1 <i>Importance of Supplier Selection in PFSCs</i>	7
2.3.2 <i>Key Criteria for Supplier Evaluation</i>	7
2.3.3 <i>Methodological Approaches to Supplier Selection</i>	9
2.3.4 <i>Challenges in Supplier Selection for PFSCs</i>	11
2.4 PRODUCTION PLANNING AND SCHEDULING IN PFSC.....	11
2.4.1 <i>Characteristics of Production Processes in PFSC</i>	12
2.4.2 <i>Methodological Approaches to Production Scheduling in PFSCs</i>	14
2.5 INVENTORY AND COLD-STORAGE MANAGEMENT FOR PFSC	15
2.5.1 <i>Foundations of Perishable Inventory Management</i>	15
2.5.2 <i>Cold Food Supply Chain Management</i>	17
2.6 ROUTING AND DISTRIBUTION IN PFSC.....	18
2.6.1 <i>Foundations of Routing in PFSCs</i>	18
2.6.2 <i>Routing Models for Perishable Products</i>	19
2.7 INTEGRATED APPROACHES IN PERISHABLE FOOD SUPPLY CHAINS.....	20
2.7.1 <i>Foundations of Integrated Production-Distribution Planning</i>	21
2.7.2 <i>Strategic and Multi-Stage Integration in PFSCs</i>	22
2.7.3 <i>Comprehensive PIRP and Resilient PFSC Frameworks</i>	23
2.7.4 <i>Research Gaps and Limitations in Existing Integrated PFSC Models</i>	24
3. METHODOLOGY.....	27
3.1 OVERVIEW OF THE BASE MODEL AND MOTIVATION FOR EXTENSION	27
3.2 PROBLEM DESCRIPTION OF THE EXTENDED MODEL.....	28
3.3 MATHEMATICAL FORMULATION OF THE EXTENDED MODEL	30
3.3.1 <i>Objective Function</i>	32
3.3.2 <i>Constraints</i>	32
3.3.3 <i>Multi-objectives solution approach</i>	39
3.4 SOLUTION APPROACH	41
3.5 CASE STUDY DESCRIPTION.....	41
3.5.1 <i>Background and Industrial Context</i>	41
3.5.2 <i>Supply Chain Structure and Planning Horizon</i>	42

3.5.3	<i>Demand Characteristics and Uncertainty</i>	43
3.5.4	<i>Key Operational Constraints</i>	44
3.5.5	<i>Purpose of the Case Study</i>	44
3.5.6	<i>Case Study Parameters</i>	45
3.5.7	<i>Sets and Indices</i>	45
4.	COMPUTATIONAL AND SENSITIVITY ANALYSIS RESULTS	48
4.1	COMPUTATIONAL RESULTS	48
4.1.1	<i>Results and Discussion of the Bi-Objective Model</i>	48
4.1.2	<i>Trade-Off Analysis of the ϵ-Constraint Model</i>	49
4.1.3	<i>Procurement Allocation and Cost Distribution</i>	50
4.1.4	<i>Procurement Distribution by Raw Material</i>	51
4.1.5	<i>Production Quantity Distribution Across Products</i>	52
4.1.6	<i>Vehicle Routing Decision</i>	53
4.2	SENSITIVITY ANALYSIS	56
4.2.1	<i>Sensitivity Analysis on DRO level</i>	56
4.2.2	<i>Sensitivity Analysis on Emission Target</i>	57
4.2.3	<i>Sensitivity Analysis on Vehicle Capacity</i>	58
4.2.4	<i>Sensitivity Analysis on Emission Factor</i>	59
5.	CONCLUSION	60
5.1	ANSWERS TO THE MAIN QUESTIONS OF THE THESIS	60
5.2	RESEARCH LIMITATIONS	60
5.3	FUTURE RECOMMENDATIONS	61
5.4	MANAGERIAL INSIGHTS	62
	APPENDIX A. SUPPLEMENTARY DATA FOR THE CASE STUDY PROBLEM	63
	APPENDIX B. THE DETAILED RESULTS OF THE CASE STUDY PROBLEM AND SENSITIVITY ANALYSES ($E = 5\%$)	68
	PROCUREMENT DECISIONS	68
	PRODUCTION RESULTS	71
	RAW MATERIAL INVENTORY	71
	ROUTING DECISION RESULTS	73
	APPENDIX C. THE DETAILED RESULTS OF THE SENSITIVITY ANALYSES	77
	DRO SENSITIVITY ANALYSIS	77
	E-CONSTRAINT SENSITIVITY ANALYSIS	78
	REFERENCES	79

List of Tables

Table 2.1 Research gap	26
Table 3.1 Sets & Indices.....	30
Table 3.2 Parameters	30
Table 3.3 Decision Variables.....	31
Table 3.4 Case study Sets.....	45
Table 3.5 Day - Dependent Mean and Standard Deviation of the probabilistic demands.....	45
Table 3.6 The set of predefined time windows for serving customers	47
Table 3.7 Summary of Supplier Parameters.....	47
Table 3.8 The production cost and time of final products	47
Table 3.9 Distance matrix between cold-storage and retailers.....	48
Table 4.1 Goal values of the bi-objective model.	48
Table 4.2 Computational results of the ε -constraint model for the case study problem.....	49
Table 4.3 Total procurement by supplier	50
Table 4.4 Total procurement by raw material	51
Table 4.5 Total production quantity	52
Table 4.6 Optimal routing decisions for each planning period	53
Table 4.7 Vehicle usage by period	55
Table 4.8 CO ₂ emissions generated by vehicle routes	55
Table 4.9 Sensitivity analysis of the DRO parameter ε	56
Table 4.10 Sensitivity analysis of the ε -constraint parameter	57
Table 4.11 Sensitivity Analysis of Vehicle Capacity on Total Cost, Carbon Emissions.....	58
Table 4.12 Impact of Vehicle Capacity on Transportation Distance and Distribution Costs	58
Table 4.13 Impact of Emission Factor on Total Cost and Emission	59
Table A.1 The travel time between cold-storage and retailers in minutes	63
Table A.2 Supplier, Raw Material Parameters and Inbound Transportation Costs.....	63
Table A.3 BOM Coefficients.....	64
Table A.4 Production and Storage Capacity Parameters	64
Table A.5 Retailer Service Times	64
Table A.6 Vehicle Fleet Characteristics.....	65
Table A.7 Goodwill Loss Parameter	65
Table A.8 Product related parameters	65
Table A.9 Global Model Parameters	65
Table A.10 The complete set of distributionally robust demand thresholds	66
Table A.11 Raw material initial inventory	67
Table A.12 Raw material holding cost.....	67
Table B.1 Detailed procurement decisions (Period t_0 - t_7)	68
Table B.2 Detailed production quantities by period	71
Table B.3 Raw material inventory holding cost period t_0 - t_7	71
Table B.4 Detailed Raw material inventory and holding cost by period.....	72
Table B.5 Fixed vehicle cost results by period	73
Table B.6 Vehicle variable routing cost results by period.....	73
Table B.7 Delivery quantities of finished products to retailers by period.....	74
Table B.8 Arrival times of vehicles at retailers for each planning period	76
Table B.9 Lateness values at retailers for each planning period.....	76
Table C.1 Detailed sensitivity analysis of the DRO parameter ε	77

Table C.2 Detailed results of the ε-Constraint Sensitivity Analysis for Cost and Emission Objectives	78
--	-----------

List of Figures

Figure 2.1 Characteristics of Perishable Food Supply Chain	5
Figure 2.2 Multi-echelon inventory system of fresh products	16
Figure 2.3 Block diagram representation of the cold chain process	18
Figure 3.1 The geographical locations of the retailers and the factory	42
Figure 4.1 Pareto Frontier Generated by the ε-Constraint Method	50
Figure 4.2 Distributionally Robust Demand Trend	52
Figure 4.3 Production quantities across planning periods	52
Figure 4.4 Period 1 (Medium Demand): 3 vehicles utilized	54
Figure 4.5 Period 2 (Peak Demand): 4 vehicles utilized	54
Figure 4.6 Period 6 (Low Demand): 2 vehicles utilized	54
Figure 4.7 Sensitivity Analysis of DRO Confidence Level.....	57

List of Abbreviations

ABM - Agent-Based Modeling
AHP - Analytic Hierarchy Process
ANP - Analytic Network Process
BNS - Bipolar Neutrosophic Sets
BOM - Bill of Materials
BWM - Best-Worst Method
CIP - Clean-in-Place
CRITIC - Criteria Importance Through Intercriteria Correlation
DES - Discrete-Event Simulation
DEMATEL - Decision-Making Trial and Evaluation Laboratory
DRCC - Distributionally Robust Chance Constraint
DRO - Distributionally Robust Optimization
EOQ - Economic Order Quantity
FAHP - Fuzzy Analytic Hierarchy Process
FEFO - First Expired, First Out
FIFO - First In, First Out
FTOPSIS - Fuzzy TOPSIS
HACCP - Hazard Analysis and Critical Control Points
ICA-SADE - Imperialist Competitive Algorithm-Self-Adaptive Differential Evolution
ILP - Integer Linear Programming
IRP - Inventory Routing Problem
IT - Information Technology
LIRP - Location-Inventory-Routing Problem
LEFO - Last Expired, First Out
LSFO - Last Stored, First Out
MARCOS - Measurement of Alternatives and Ranking according to COmpromise Solution
MCDM - Multi-Criteria Decision Making
MINLP - Mixed-Integer Nonlinear Programming
MTZ - Miller-Tucker-Zemlin (subtour elimination)
PIRP - Production-Inventory-Routing Problem
PF-TOPSIS - Pythagorean Fuzzy TOPSIS
PVRP - Perishable Vehicle Routing Problem
PSO-SA - Particle Swarm Optimization-Simulated Annealing
RFID - Radio-Frequency Identification
RTI - Returnable Transport Items
SCND - Supply Chain Network Design
SFS - Spherical Fuzzy Sets
SMEs - Small and Medium-sized Enterprises
SOC - Second-Order Cone
TDVRP - Time-Dependent Vehicle Routing Problem
TOPSIS - Technique for Order Preference by Similarity to Ideal Solution
TTI - time-temperature indicators
IoT - Internet of Things
VRP - Vehicle Routing Problem
VRPTW - Vehicle Routing Problem with Time Windows
WGP - Weighted Goal Programming

1. Introduction

1.1 Background

The management of PFSCs is especially complex because food products deteriorate over time and are highly sensitive to storage and handling conditions. Fresh produce, dairy products, meat products, and ready-to-eat meals are subject to continuous biological and chemical deterioration, which can accelerate under unsuitable storage, transportation, or handling conditions (Entrup et al., 2004). As product quality declines, freshness, nutritional value, and food safety may be compromised (Amorim et al., 2012). Consequently, maintaining appropriate conditions throughout the cold chain is essential for preserving product quality and reducing waste (Shi et al., 2024).

Cold-chain systems play a critical role in supporting PFSC operations. However, these systems are energy-intensive and vulnerable to disruptions such as temperature deviations, transportation delays, and equipment failures. Such disruptions may result in product deterioration before products reach consumers and contribute to substantial food losses. According to (Parfitt et al., 2010), approximately one-third of food produced for human consumption is lost or wasted across the supply chain.

Effective coordination of procurement, production, inventory, and distribution activities is therefore essential in PFSCs. Poor coordination among these decision areas can lead to stockouts, excess inventory, spoilage, and unnecessary operational costs, ultimately affecting both profitability and sustainability (Govindan et al., 2014). At the same time, increasing consumer expectations regarding freshness, product quality, transparency, and environmental responsibility place additional pressure on food companies to improve supply chain performance.

These challenges are particularly significant for SMEs. Compared with larger organizations, SMEs often operate with limited production capacity, constrained infrastructure, and fewer financial and technological resources. In addition, they must cope with fluctuations in supply and demand, seasonal effects, and uncertainties associated with transportation and cold-chain operations (J. Sharma et al., 2024). Such conditions make planning and decision-making considerably more difficult.

As a result, there is increasing interest in optimization approaches that support coordinated decision-making under uncertainty. Integrating procurement allocation, production planning, inventory management, and distribution decisions can improve the overall performance of PFSCs by reducing waste, improving product availability, and utilizing resources more efficiently. This need has motivated the development of integrated optimization models that better represent the operational characteristics and uncertainty inherent in PFSCs.

1.2 Problem Context and Motivation

Despite the importance of effective coordination in PFSCs, procurement, production, inventory, and distribution decisions are often planned independently. Procurement activities typically focus on supplier capacities, costs, and material availability, while production planning aims to satisfy demand within available resources. Distribution decisions are frequently based on vehicle availability, customer locations, and delivery requirements.

Although these decisions are closely interconnected, they are commonly addressed in separate planning processes. Such a fragmented approach may result in inefficiencies throughout the supply chain, as decisions made at one stage directly influence inventory levels, production feasibility, transportation requirements, and product freshness.

The challenges associated with PFSC planning become even more significant under uncertainty. Demand levels may fluctuate over time, supplier deliveries may vary in quantity and timing, and transportation activities can be affected by operational disruptions. Furthermore, perishable products continuously lose value as they move through the supply chain. Traditional deterministic models often assume that all parameters are known with certainty and therefore may underestimate operational risks. Although stochastic approaches can represent uncertainty explicitly, they generally require probability distributions that are difficult to estimate reliably, particularly for SMEs with limited historical data.

These characteristics highlight the importance of integrated planning approaches that simultaneously consider multiple supply chain decisions. Coordinating procurement allocation, production planning, inventory management, and routing activities within a unified framework can improve resource utilization, reduce waste, and support more effective decision-making. In PFSCs, such coordination is especially important because delays or inefficiencies in one stage can quickly affect product quality, shelf life, and customer service performance.

Several integrated optimization models have been proposed in the literature to address these challenges. Among them, the ISSPRP developed by (Hashemi-Amiri et al., 2023b) represents an important contribution by integrating procurement, production, and distribution decisions within a single optimization framework. However, several limitations remain. Existing models often simplify production structures, omit explicit consideration of finished-goods cold-storage, or rely on simplified assumptions regarding perishability. Environmental impacts associated with transportation activities, such as CO₂ emissions, are also frequently excluded from decision-making models. In addition, many studies are validated using synthetic data sets, while applications based on real operational data remain relatively limited, particularly for SMEs.

These limitations provide the motivation for the development of the EIPAPPRP proposed in this thesis. Building upon the foundation established by previous integrated models, the EIPAPPRP incorporates BOM, explicit cold-storage operations, and transportation-related CO₂ emissions within a unified optimization framework. Furthermore, uncertainty is addressed through DRO, allowing the model to generate robust decisions under a range of plausible supply and demand conditions. By incorporating these additional operational characteristics, the proposed model aims to provide a more realistic representation of PFSC planning problems and support decision-making in environments characterized by uncertainty and limited resources.

1.3 Research Question and Objectives

This thesis builds upon the ISSPRP proposed by (Hashemi-Amiri et al., 2023) and develops the Extended Integrated Procurement Allocation, Production Planning, and Routing Problem (EIPAPPRP). The proposed model incorporates additional operational characteristics that are relevant to PFSCs, including multi-ingredient production through BOM, explicit cold-storage operations, and transportation-related CO₂ emissions. To improve decision-making under

uncertainty, the model integrates DRO and is evaluated using real operational data from a Mongolian ready-to-eat meal manufacturer.

- **Research Question**

How can the ISSPRP proposed by (Hashemi-Amiri et al., 2023) be extended to better represent the operational characteristics of PFSCs under demand uncertainty, and how can the resulting EIPAPPRP be applied to support integrated planning decisions in a real-world SMEs food manufacturing enterprise?

- **Objectives**

1. Develop the EIPAPPRP by extending the ISSPRP proposed by (Hashemi-Amiri et al., 2023) and adapting it to reflect the operational characteristics of a real food manufacturing SMEs.
2. Incorporate BOM, finished-goods cold-storage, and transportation-related CO₂ emissions into the integrated optimization framework.
3. Apply DRO to address uncertainty in supply and demand.
4. Evaluate the applicability of the EIPAPPRP using real operational data from a Mongolian ready-to-eat meal manufacturing SMEs.
5. Assess the operational, economic, and environmental performance of the EIPAPPRP under different uncertainty scenarios.
6. Examine the potential benefits of integrated planning for improving coordination and supporting sustainable decision-making in PFSCs.

1.4 Thesis Structure

- **Chapter 1** introduces PFSCs, presents the problem context and motivation, and defines the research question and objectives of the thesis.
- **Chapter 2** reviews the relevant literature on PFSCs, including procurement, production planning, inventory and cold-storage management, routing decisions, and integrated optimization approaches.
- **Chapter 3** presents the EIPAPPRP, including the model assumptions, mathematical formulation, solution approach, and case study description.
- **Chapter 4** reports the computational results and sensitivity analyses and evaluates the performance of the EIPAPPRP under different uncertainty scenarios.
- **Chapter 5** summarizes the main findings, discusses research limitations, provides recommendations for future research, and presents managerial insights.

2. Literature Review

2.1 Introduction to the Literature Review

This chapter reviews the literature relevant to planning and decision-making in PFSCs. The review focuses on the operational characteristics of PFSCs and the main decision areas addressed in this thesis, including procurement, production planning, inventory and cold-storage management, routing, and integrated optimization approaches. Particular attention is given to the effects of perishability, uncertainty, and sustainability requirements on supply chain performance.

PFSCs involve multiple interrelated decisions that influence product quality, operational efficiency, and environmental performance. As a result, researchers have increasingly investigated integrated planning approaches that coordinate activities across different stages of the supply chain. Understanding the strengths and limitations of these approaches is important for identifying research gaps and motivating the development of the EIPAPPRP proposed in this thesis.

The remainder of this chapter is organized as follows. Section 2.2 presents the key characteristics of PFSCs, including perishability, quality deterioration, shelf-life constraints, and the operational challenges associated with managing food products throughout the supply chain. Section 2.3 reviews the literature on supplier selection and order allocation in PFSCs, highlighting commonly used evaluation criteria, decision-making methods, and the limitations of existing approaches. Section 2.4 examines production planning studies, with particular attention to capacity management, demand fulfillment, and planning decisions relevant to perishable products.

Section 2.5 discusses inventory and cold-storage management, focusing on inventory control policies, storage capacity considerations, and strategies for reducing product deterioration and waste. Section 2.6 reviews routing and distribution planning in PFSCs, including vehicle routing models, delivery scheduling, and approaches for maintaining product quality during transportation. Finally, Section 2.7 analyzes integrated optimization approaches and identifies research gaps and limitations that motivate the development of the EIPAPPRP proposed in this thesis.

2.2 Foundations of Perishable Food Supply Chains

PFSCs are characterized by operational challenges that distinguish them from conventional supply chains. Unlike non-perishable products, food products undergo continuous biological and chemical deterioration throughout production, storage, transportation, and retail operations. Consequently, decision-making in PFSCs must account for perishability, quality degradation, cold-chain requirements, demand variability, and regulatory constraints. These characteristics increase planning complexity and highlight the importance of coordinated decision-making across supply chain activities. Understanding these characteristics provides the foundation for analyzing optimization approaches developed for PFSCs.

2.2.1 Perishability and Core Characteristics of PFSCs

PFSCs have several characteristics that influence operational planning and distinguish them from non-perishable supply chains. These characteristics affect procurement, production, inventory management, and distribution decisions and contribute to the complexity of PFSC

operations.

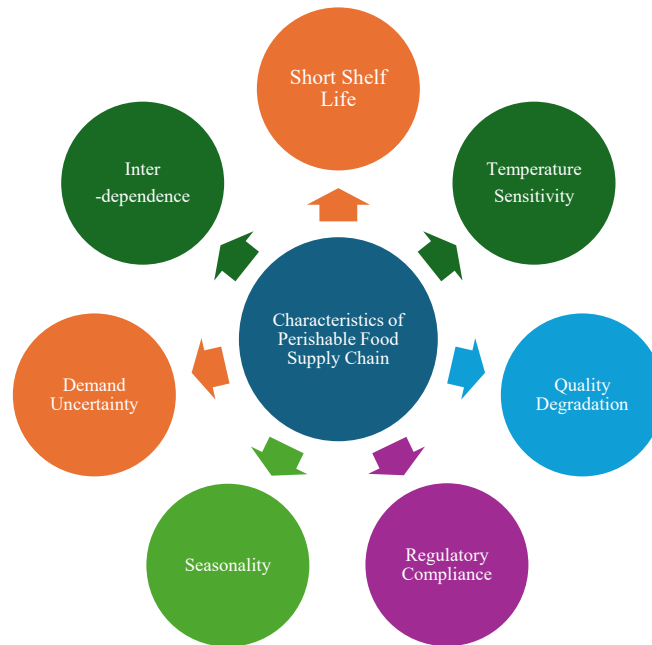


Figure 2.1 Characteristics of Perishable Food Supply Chain

Source: These characteristics, synthesized from diverse PFSC literature, collectively illustrate the operational challenges inherent to perishable food supply chains

- **Short Shelf Life**

Perishable foods have a short shelf life due to physico-chemical changes and microbiological factors during storage. These changes lead to sensory deterioration, necessitating careful monitoring and control of environmental conditions to maintain quality and safety throughout their shelf life (Valero et al., 2012). Given the accelerated rate at which perishable products degrade, maintaining minimal lead times from production to end-use is essential. Even small disruptions can amplify spoilage rates and generate avoidable economic losses (Amorim et al., 2012).

- **Temperature Sensitivity**

Perishable foods are highly temperature-sensitive, requiring strict thermal control to slow biochemical and microbial decay (Xu et al., 2020). Even small temperature excursions during storage, handling, or transport can accelerate quality deterioration, shorten shelf life, and increase food-safety risks (Jedermann et al., 2014). Breaks in the cold chain, such as temperature spikes during loading or en route fluctuations, are consistently identified as major contributors to waste and compromised product integrity (Jedermann et al., 2009). These challenges highlight the critical need for reliable temperature-management systems across the entire cold chain.

- **Continuous Quality Degradation**

Even under ideal storage conditions, perishable foods experience continuous biochemical and physical deterioration that progressively reduces freshness, nutritional value, and consumer acceptability (Xu et al., 2020). This decline in quality directly affects demand and pricing as

products lose sensory attributes over time (He et al., 2018). The perishability process is inherently dynamic and accelerates based on environmental conditions such as temperature and humidity, as demonstrated in supply chain quality-decay modelling approaches (Rong et al., 2011). Consequently, continuous monitoring and quality-tracking systems are important for reducing spoilage and maintaining acceptable freshness levels.

- **Regulatory Requirements**

Regulatory compliance plays a central role in perishable food supply chains, as firms must demonstrate that products remain safe, traceable, and properly handled throughout their movement from suppliers to end consumers. These regulations increasingly require continuous monitoring of environmental conditions, documentation of handling activities, and verification of temperature-control standards to ensure that no stage of the chain exposes products to unsafe conditions (Y. Wang et al., 2015). As discussed earlier regarding their temperature sensitivity, perishables require close environmental control, which is why regulators increasingly emphasize real-time monitoring capabilities and accurate documentation to identify unsafe deviations at the earliest stage (Xu et al., 2020). For many companies, especially SMEs, these requirements introduce operational challenges, as maintaining compliant monitoring systems, digital traceability tools, and reliable cold-chain practices demands both technological investment and organizational capacity (J. Wang et al., 2015). As a result, regulatory requirements influence both operational practices and technology adoption within PFSCs.

- **Seasonality and Supply Variability**

Seasonality is a defining characteristic of many agricultural and fresh food supply chains, as production cycles naturally rise and fall throughout the year, shaping both the volume and quality of products available in the market. These seasonal patterns influence harvesting schedules, post-harvest handling needs, and the timing of supply chain activities, making it difficult for firms to maintain stable production and distribution plans during off-peak periods (Orjuela-Castro et al., 2017). In addition to predictable seasonal cycles, external environmental factors such as weather variability, pest outbreaks, and crop diseases further disrupt supply by altering yields, influencing product condition, and reducing the reliability of upstream sourcing (Kumar & Agrawal, 2023). These fluctuations create significant uncertainty for producers and retailers who must adapt procurement quantities, storage strategies, and inventory levels to match inconsistent supply conditions throughout the year (Boiteau & Pingali, 2022).

- **Demand Uncertainty**

Demand for perishable products is inherently volatile, shaped by seasonal consumption patterns, shifting consumer preferences, and market-driven factors such as promotions or price changes. External disruptions, including events like COVID-19, introduce sudden shocks that further complicate demand planning and create abrupt fluctuations in purchasing behavior (Kumar et al., 2021). Due to their limited shelf life, even modest forecasting errors can quickly translate into waste or shortages, making demand management considerably more challenging than in non-perishable product categories (Mousavi et al., 2022). These uncertainties require PFSCs to adopt flexible planning methods and responsive distribution strategies to adjust to rapid changes in market conditions.

- **High Interdependence of Decisions**

Decisions in perishable food supply chains are highly interdependent, meaning choices made at one stage directly affect the feasibility and performance of subsequent stages. Supplier reliability influences production timing and inventory freshness, while production schedules must be aligned with distribution capacity and routing constraints to prevent delays or excessive spoilage. Research consistently shows that managing procurement, production, inventory, and transportation separately leads to mismatches such as overproduction, unnecessary waste, or unmet demand (Hashemi-Amiri et al., 2023). Similarly, studies on integrated routing and production planning highlight that without coordination, routing delays can undermine production efficiency and reduce product quality upon delivery (Vahdani et al., 2017). These interdependencies make integrated decision-making essential for achieving freshness, minimizing waste, and ensuring operational efficiency in PFSCs.

Together, the scientific literature portrays PFSCs as complex, time-sensitive systems shaped by biological degradation, environmental sensitivity, demand and supply uncertainty, stringent regulatory requirements, and structural limitations. These systemic characteristics explain why PFSC decision-making models must incorporate perishability dynamics, temperature dependence, operational interdependencies, and uncertainty, elements that motivate the need for integrated and robust modeling approaches.

2.3 Supplier Selection and Order Allocation in PFSCs

2.3.1 Importance of Supplier Selection in PFSCs

Supplier selection is a critical strategic decision in perishable food supply chains because supplier performance directly influences raw material freshness, shelf life, production feasibility, and overall supply chain responsiveness. Unlike durable goods, perishables deteriorate continuously, which makes procurement timing, cold-chain integrity, and delivery reliability particularly important (Xu et al., 2020). The selection of inappropriate or unreliable suppliers can lead to reduced product quality, increased waste, and higher operational costs. Therefore, supplier selection in PFSCs must account for both traditional economic criteria and perishability-specific requirements that determine downstream operational performance.

2.3.2 Key Criteria for Supplier Evaluation

While cost remains an important consideration, PFSCs require a broader evaluation of supplier capabilities. The literature consistently emphasizes that quality and delivery performance outweigh purely economic criteria in perishable contexts (Ho et al., 2010).

- **Quality and Food Safety**

In PFSCs, quality and food safety are among the most important criteria in supplier evaluation because the condition of raw materials directly influences production performance, product quality, and consumer safety. Unlike non-perishable products, food products are highly sensitive to handling practices, storage conditions, and temperature control throughout the supply chain. Consequently, suppliers are expected to maintain effective quality-management systems, comply with recognized food-safety standards, and implement reliable cold-chain practices (Wallace et al., 2018).

The literature emphasizes that supplier performance should be evaluated not only on the quality of delivered materials but also on operational reliability, including the ability to maintain temperature integrity during storage and transportation (Trienekens & Zuurbier, 2008). Advances in monitoring technologies, such as time-temperature indicators (TTIs), Internet of Things (IoT) sensors, and traceability systems, have further improved the ability to detect and respond to quality deviations throughout the supply chain (Aung & Chang, 2014). Suppliers capable of providing consistent product quality, transparent information sharing, and effective quality-control procedures are generally preferred because these capabilities contribute to food safety, waste reduction, and overall supply chain performance.

- **Delivery Reliability and Lead Time**

Delivery reliability is a decisive supplier selection criterion in PFSCs because lead-time variability directly interacts with temperature-dependent deterioration dynamics, often amplifying spoilage rates in non-linear ways. Recent models show that a delay of even a slight shift products into significantly higher deterioration states, especially under Arrhenius-based or exponential decay functions used in temperature-sensitive goods (Jedermann et al., 2014). When deliveries fail to meet planned arrival times, production sequences must be rescheduled, batch sizes may fall below economically viable thresholds, or materials must be discarded when they breach freshness or safety constraints (Alvarez et al., 2020). Also, PFSC firms increasingly evaluate suppliers not by nominal lead time alone but by lead-time variance, on-time delivery probability, and their ability to synchronize arrivals with temperature-dependent processing and distribution cycles, parameters identified as critical in preventing cascading quality degradation across the chain (Hashemi-Amiri et al., 2023).

- **Geographic Proximity**

Geographic proximity is an important consideration in supplier evaluation because it influences transportation time, logistics costs, and the condition of raw materials upon arrival. In PFSCs, shorter transportation distances can help preserve product freshness, reduce the risk of quality deterioration during transit, and improve the reliability of material deliveries. Closer suppliers may also facilitate better coordination between procurement, production, and distribution activities by reducing lead times and increasing planning flexibility (Navazi et al., 2021).

In addition to operational benefits, shorter transportation distances can contribute to lower transportation-related emissions and reduced refrigeration requirements during transit. However, relying excessively on suppliers located within the same geographic area may increase vulnerability to regional disruptions such as adverse weather conditions, infrastructure failures, or localized supply shortages. For this reason, the literature suggests that proximity should be considered together with supply reliability and diversification objectives when evaluating supplier alternatives (Hashemi-Amiri et al., 2023). Therefore, geographic proximity can improve both operational efficiency and product freshness, but it should be balanced against supply chain resilience considerations.

- **Sustainability Practices**

Sustainability has become an increasingly important consideration in supplier evaluation within PFSCs, reflecting growing environmental, social, and economic concerns throughout the food supply chain. The literature commonly assesses sustainability through environmental indicators, such as CO₂ emissions, energy consumption, water usage, and waste generation, as

well as social and economic factors, including labor practices, food safety compliance, and long-term business viability (R. Sharma et al., 2024). As a result, supplier assessment has gradually expanded beyond traditional cost and quality criteria to incorporate broader sustainability objectives.

In PFSCs, sustainability is particularly relevant because supplier practices can influence food waste, transportation efficiency, energy requirements, and overall supply chain performance. Suppliers that adopt environmentally responsible production methods, reduce resource consumption, and support efficient cold-chain operations can contribute to lower environmental impacts while maintaining product quality and freshness (Banaeian et al., 2018). Consequently, sustainability considerations are increasingly integrated into supplier evaluation frameworks, reflecting their role in supporting both operational performance and long-term supply chain resilience.

- **Flexibility and Responsiveness**

Flexibility and responsiveness are increasingly recognized as important criteria in supplier evaluation, particularly in PFSCs where demand, supply conditions, and operational requirements can change rapidly. Responsive suppliers contribute to supply chain performance through reliable communication, the ability to adjust delivery schedules, and the capacity to accommodate changes in order quantities or delivery requirements under uncertain conditions (R. Sharma et al., 2024). These capabilities support continuity of operations and help firms respond more effectively to disruptions.

In PFSCs, flexibility is especially important because delays, quality issues, transportation disruptions, or unexpected changes in demand can quickly affect product freshness and availability. Suppliers capable of adjusting deliveries, coordinating corrective actions, and responding promptly to operational changes can help reduce the impact of such disruptions on downstream activities (Crivei et al., 2025). Recent studies also emphasize responsiveness indicators such as lead-time adjustment capability, information-sharing effectiveness, and the ability to manage variable order quantities, all of which contribute to improved coordination across procurement, production, and distribution processes (Görçün et al., 2023). Consequently, flexibility and responsiveness play an important role in maintaining service levels, reducing operational risks, and supporting efficient supply chain performance in PFSCs.

These criteria reflect the operational characteristics of PFSCs and illustrate why supplier evaluation is often more complex than in conventional supply chains.

2.3.3 Methodological Approaches to Supplier Selection

A wide range of methodological approaches has been proposed to support supplier selection in perishable food supply chains (PFSCs). Due to the multiple and often conflicting criteria involved in supplier evaluation, including cost, quality, food safety, delivery performance, sustainability, and cold-chain capabilities, supplier selection is commonly formulated as a multi-criteria decision-making problem (Handayani et al., 2025). Consequently, Multi-Criteria Decision-Making (MCDM) techniques have become one of the most widely adopted approaches in the supplier-selection literature.

Among traditional MCDM methods, the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are frequently applied to

evaluate and rank suppliers according to multiple performance criteria (Handayani et al., 2025). AHP is commonly used to determine the relative importance of evaluation criteria, whereas TOPSIS ranks suppliers based on their distance from ideal and non-ideal solutions (Banaeian et al., 2018). These approaches are particularly suitable for PFSCs because supplier evaluation extends beyond economic considerations to include freshness preservation, food safety, delivery reliability, and temperature-control capabilities.

Because many supplier-evaluation criteria involve subjective judgments and uncertain information, researchers have increasingly adopted fuzzy MCDM approaches. Methods such as Fuzzy AHP (FAHP) and Fuzzy TOPSIS (FTOPSIS) incorporate linguistic assessments and uncertainty into the decision-making process, allowing expert knowledge to be represented more realistically than conventional numerical scales (Mohammed et al., 2023). More advanced extensions, including Pythagorean fuzzy and neutrosophic approaches, have been proposed to improve the representation of ambiguity, hesitation, and incomplete information when assessing sustainability practices, cold-chain compliance, and quality-management capabilities (Hajiaghaei-Keshteli et al., 2023; Sahoo & Debnath, 2026).

In addition to conventional and fuzzy MCDM approaches, hybrid evaluation frameworks have been developed to improve the robustness of supplier assessment. Methods such as Criteria Importance Through Intercriteria Correlation (CRITIC), Measurement of Alternatives and Ranking According to Compromise Solution (MARCOS) (Y. Wang et al., 2024), Decision-Making Trial and Evaluation Laboratory (DEMATEL), Best-Worst Method (BWM), and Analytic Network Process (ANP) have been employed to derive criterion weights, evaluate interdependencies among criteria, and improve ranking reliability under uncertainty (R. Sharma et al., 2024). These methods are particularly useful when supplier performance depends on multiple interconnected operational, environmental, and quality-related factors.

While these approaches provide effective tools for evaluating and ranking suppliers, they do not determine how procurement quantities should be distributed among selected suppliers. This limitation has motivated the development of procurement allocation models that complement supplier evaluation with quantity allocation decisions. Unlike supplier evaluation methods that focus primarily on identifying suitable suppliers, procurement allocation models determine the quantity assigned to each supplier and, in multi-period settings, the timing of procurement decisions across the planning horizon (Aouadni et al., 2019). Procurement allocation has attracted increasing attention in the literature because supplier selection and order allocation are recognized as two key strategic purchasing decisions that jointly influence sourcing performance and supply chain efficiency (Aouadni et al., 2019).

To address these challenges, various methodological approaches have been proposed in the literature. (Mohammed et al., 2018) developed a sustainable supplier selection and order allocation model using a multi-objective mathematical programming framework combined with a hybrid solution approach to simultaneously address economic, environmental, and social objectives. (Hosseini et al., 2019) proposed a resilient supplier selection and optimal order allocation model under disruption risks, employing robust optimization techniques to improve supply chain resilience under uncertainty. Similarly, (Mohammed et al., 2023) introduced a resilient multi-tier supplier selection and order allocation framework for the food industry, integrating resilience considerations with supplier evaluation and allocation decisions through a hybrid methodology. These studies demonstrate a gradual shift from standalone supplier evaluation toward integrated optimization frameworks that jointly address supplier selection

and procurement allocation under multiple operational objectives. Such developments provide an important methodological foundation for integrated procurement planning in PFSCs.

2.3.4 Challenges in Supplier Selection for PFSCs

Despite the development of numerous supplier evaluation methods, supplier selection in PFSCs remains challenging due to a combination of structural, informational, and operational constraints. A persistent challenge is the lack of real-time data and limited traceability, which restricts visibility into supplier handling practices and quality consistency, an issue especially pronounced in fragmented agro-food networks (Ho et al., 2010). SMEs face additional difficulties because cost-quality trade-offs are more acute for perishables: low-cost options often imply compromised cold-chain capabilities or longer lead times, both of which accelerate deterioration. Regulatory pressures further intensify supplier scrutiny, as compliance with food safety, hygiene, and thermal-control standards imposes substantial monitoring and verification requirements (Crivei et al., 2025).

In addition, PFSCs are highly exposed to demand-supply mismatches, seasonality, and weather-driven disruptions, requiring suppliers to remain adaptable in quantities, delivery frequencies, and timing, capabilities not consistently available across all vendors. Digitalization gaps also persist: many suppliers lack integrated IT or temperature-monitoring systems, limiting their ability to provide reliable, time-stamped data on storage or transport conditions (R. Sharma et al., 2024). Finally, competency and capability gaps remain common, as some suppliers do not maintain standardized cold-chain processes, quality-control routines, or sustainability practices required in PFSCs (Görçün et al., 2023).

Taken together, these challenges reveal that supplier selection in PFSCs is constrained not only by perishability-driven operational complexity but also by broader limitations in data quality, technological maturity, regulatory compliance capacity, seasonality-related volatility, and supplier adaptability. These constraints reinforce the need for robust evaluation frameworks and highlight the limitations of treating supplier selection as an isolated decision problem. As a result, recent research has increasingly shifted toward integrated supplier selection, procurement allocation, production planning, and distribution models that better capture the operational interdependencies of PFSCs, as discussed in Section 2.7.

2.4 Production Planning and Scheduling in PFSC

Production planning in PFSCs is considerably more complex than in traditional manufacturing systems due to the continuous deterioration of product quality, strict temperature requirements, and tight synchronization needs between processing, storage, and distribution. Unlike durable products, perishables lose value rapidly as a function of time and environmental exposure, which imposes narrow production-dispatch windows and heightens the importance of precise scheduling. Lead-time variability, supplier delivery uncertainty, and temperature-dependent quality decay further constrain feasible production plans, requiring planning approaches that account for perishability, variability, and close interdependence with inventory and routing decisions. Against this backdrop, the following subsections review the main characteristics, methods, and challenges associated with production planning in PFSCs.

2.4.1 Characteristics of Production Processes in PFSC

Production processes in PFSCs are defined by biological decay, thermal sensitivity, strict temporal coordination, and multi-stage transformation. Unlike durable manufacturing, where production efficiency is measured mainly by cost and throughput, PFSC production must preserve freshness, guarantee food safety, and synchronize with cold-chain logistics. The following characteristics reflect the theoretical and operational foundations documented in the literature.

- **Time-Dependent Quality Deterioration**

Perishable food products experience continuous quality deterioration throughout the production process. Quality degradation may occur during cooking, cooling, mixing, fermentation, batching, and temporary waiting periods between processing stages. The rate of deterioration depends on both processing duration and environmental conditions, particularly temperature, which directly influence microbial activity, biochemical reactions, and product stability. Consequently, production activities affect not only manufacturing efficiency but also the remaining shelf life, freshness, and safety of finished products (Chen et al., 2009).

The literature emphasizes that quality deterioration in PFSCs should be viewed as a dynamic process that accompanies production rather than a condition that begins after manufacturing is completed. Studies demonstrate that temperature fluctuations and processing delays can accelerate microbial growth and other deterioration mechanisms, leading to quality losses and reduced consumer acceptability (Jacxsens et al., 2002). For temperature-sensitive products, even short waiting times between production stages may significantly affect the quality of intermediate and finished products. Therefore, production planning decisions must account not only for production efficiency and capacity utilization but also for their implications for freshness preservation and product quality throughout the production cycle.

- **Quality Preservation Requirements in Production Scheduling**

Unlike conventional production scheduling models, many PFSC scheduling frameworks explicitly incorporate quality-deterioration functions to represent freshness loss throughout processing, waiting, and temporary storage stages. The literature commonly applies exponential, Weibull, logistic, and temperature-dependent Arrhenius-type decay functions to model the relationship between processing conditions and product quality over time. Because deterioration is often nonlinear, even short delays may result in disproportionate reductions in remaining shelf life once critical temperature or time thresholds are exceeded. Consequently, production scheduling decisions in PFSCs extend beyond traditional objectives such as makespan minimization or resource utilization and must simultaneously consider freshness preservation and quality retention. These characteristics have motivated the development of scheduling models in which quality deterioration is directly embedded within production constraints and objective functions (Y. Li et al., 2016).

- **Freshness-driven prioritization and dynamic job sequencing**

The continuous decline in product quality also affects the sequencing of production activities. In contrast to traditional manufacturing environments, where jobs are commonly prioritized according to processing times or due dates, PFSC production systems frequently incorporate

freshness-related considerations into scheduling decisions. Products with shorter remaining shelf life, higher deterioration rates, or stricter delivery requirements often require earlier processing to reduce quality losses and maintain market value. As product conditions evolve throughout the planning horizon, production priorities may also change dynamically, requiring scheduling systems to continuously adapt to updated freshness information. This characteristic distinguishes PFSC scheduling from conventional production environments and highlights the importance of integrating quality status into production-control decisions (Steinbacher et al., 2023).

- **Tight interdependence between production completion times, cold-storage, and outbound routing**

Product deterioration does not stop at the end of processing but continues throughout storage and distribution. Consequently, production completion times, cooling operations, and vehicle departures must be carefully coordinated to preserve freshness and maintain service levels. The integrated model by (Devapriya et al., 2017) shows that even minor misalignment between production completion and vehicle departure leads to significant freshness loss and infeasible deliveries.

Similarly, coordinated production-inventory-routing models indicate that cold-storage delays increase energy consumption and reduce shelf life, creating a tri-layer synchronization problem where production, cooling, and routing are inseparable.

- **Heterogeneous machines, sanitation cycles, and allergen-handling constraints**

Food-processing facilities often operate with heterogeneous machines that differ in processing capacities, operating speeds, temperature requirements, and product compatibility. In addition, production environments must comply with sanitation procedures, allergen-segregation requirements, and cleaning-in-place (CIP) protocols between production batches. These requirements introduce sequence-dependent setup times and changeover operations that significantly increase scheduling complexity (Soler et al., 2021).

Production changeovers in food-processing systems frequently require different preparation and cleaning activities depending on the sequence of products being processed. As a result, setup times are often asymmetric and may substantially influence feasible batch sequences, machine utilization, and production efficiency. To better represent these operational realities, recent production-planning models explicitly incorporate sanitation, cleaning, and machine-compatibility constraints into scheduling decisions (Soler et al., 2021).

- **Multi-ingredient and multi-level production dependent on BOM**

PFSC production frequently involves multiple raw materials and intermediate products organized through hierarchical BOM. Products such as ready-to-eat meals, dairy products, and bakery items often require intermediate components, including sauces, fillings, marinades, or doughs, which must be produced before final assembly. Because these intermediate products are also perishable, their quality may deteriorate before they are incorporated into downstream production stages. Multi-level lot-sizing models demonstrate that ingredient perishability imposes synchronization constraints across production levels, as delays in downstream stages may cause upstream components to expire or drop below acceptable quality thresholds (Acevedo-Ojeda & Chen, 2020). As a result, BOM structures in PFSCs do not simply define

material requirements, they encode time-dependent perishability dependencies that shape feasible production schedules.

Together, these characteristics demonstrate that production planning in PFSCs is shaped by quality deterioration, temperature sensitivity, food-safety requirements, multi-stage synchronization, heterogeneous processing resources, and ingredient perishability. These factors introduce operational constraints that extend beyond traditional capacity and scheduling considerations, requiring production-planning models to explicitly account for freshness preservation and coordination across multiple supply chain activities.

2.4.2 Methodological Approaches to Production Scheduling in PFSCs

Production planning and production scheduling represent two closely related but distinct streams of research in PFSCs. Production planning primarily focuses on lot-sizing, batch-sizing, and resource-allocation decisions over a planning horizon, whereas production scheduling determines the timing and sequencing of production activities at the operational level (Amorim et al., 2013); (Marinelli et al., 2007). In PFSC environments, both decision layers must account for product deterioration, limited shelf life, and quality loss, factors that substantially increase planning complexity compared with conventional production systems.

Within the production-planning literature, significant attention has been devoted to integrating perishability into lot-sizing and inventory decisions. Classical deteriorating-inventory and Economic Order Quantity (EOQ) extensions demonstrate how replenishment policies, holding decisions, and production quantities are influenced by quality degradation over time (Giri & Chaudhuri, 1998; Muriana, 2016; Padmanabhan & Vrat, 1995). Subsequent studies further incorporated production and deterioration interactions into lot-sizing decisions (Abad, 2003; Goyal & Giri, 2003; Teng et al., 2007). More recent contributions, such as the two-phase planning framework proposed by (Shin et al., 2019), show that production decisions made in early stages directly influence the remaining shelf life and market value of finished products. These studies establish the theoretical foundation for deterioration-aware production planning in PFSCs.

Production-scheduling research focuses on determining feasible production sequences and timing decisions under perishability constraints. Early food-processing scheduling models demonstrated the necessity of simultaneously considering machine availability, labor requirements, and inventory conditions when constructing production schedules (Tadei et al., 1995). More recent studies have incorporated freshness-driven sequencing rules, where production priorities depend on remaining shelf life, deterioration rates, or quality sensitivity rather than processing times alone. For example, (Steinbacher et al., 2023) developed a flexible job-shop scheduling model showing that freshness-oriented sequencing can significantly increase the proportion of sellable output. Similarly, (Vahdani et al., 2017) incorporated temperature-dependent deterioration functions directly into scheduling decisions, demonstrating that thermal exposure during processing and intermediate waiting periods substantially affects product quality. In parallel, stochastic and lifespan-aware scheduling approaches recognize that deterioration rates and remaining shelf life are often uncertain and influenced by environmental conditions. The framework proposed by (Komijani & Sheikh Sajadieh, 2024) illustrates how neglecting freshness variability may lead to infeasible schedules, while (Pratap et al., 2022) incorporate uncertainty in processing and distribution activities to improve operational robustness.

The most advanced methodological developments integrate production planning and scheduling decisions with downstream logistics activities. Rather than optimizing production and distribution separately, these models jointly determine production quantities, processing sequences, storage durations, and transportation decisions. The integrated model developed by (H.-K. Chen et al., 2009) demonstrates how misalignment between production completion times and delivery schedules can increase spoilage and reduce overall system performance. Subsequent studies extended this integration to multi-plant environments, temperature-dependent transportation systems, and sustainability-oriented distribution networks (Karaoğlu et al., 2024; F. Wang et al., 2025). Due to the high computational complexity of these integrated formulations, researchers frequently employ decomposition methods, metaheuristics, and hybrid solution approaches to obtain high-quality solutions within practical computational times.

Taken together, the literature demonstrates a clear methodological evolution from deterioration-aware lot-sizing models, to freshness-driven scheduling approaches, and ultimately to integrated production-distribution frameworks. This progression reflects the growing recognition that production decisions in PFSCs cannot be separated from product quality dynamics, uncertainty, and downstream logistics interactions, providing an important foundation for the integrated optimization model developed in this thesis.

2.5 Inventory and Cold-Storage Management for PFSC

2.5.1 Foundations of Perishable Inventory Management

Effective inventory management is central to reducing waste, preserving product quality, and ensuring product availability in PFSCs. Empirical studies show that well-designed inventory policies can reduce spoilage, improve freshness, and increase customer satisfaction by ensuring that products reach consumers with sufficient remaining shelf life (Martin & Iravo, 2014). (Martin & Iravo, 2014). In supermarkets, poor rotation and inadequate monitoring can lead to spoilage rates of up to 15% for perishables, directly undermining profitability (Ketzenberg, 2006). Conversely, optimized inventory systems enhance freshness and shelf availability, which are among the strongest drivers of consumer purchasing behavior for food products (Orjuela Castro & Jaimes, 2017). Consequently, inventory management in PFSCs encompasses decisions regarding replenishment quantities, storage conditions, inventory age, and product issuing policies, with the objective of balancing inventory holding costs against spoilage and stockout risks (Z. Chen, 2018; Shashi et al., 2021).

The importance of inventory management in PFSCs stems from the deterioration behavior of perishable products. The literature commonly distinguishes between two broad categories of perishables. The first includes products with fixed shelf lives, where items remain usable until reaching a predetermined expiration date. The second includes products subject to continuous deterioration, where biochemical and microbiological processes gradually reduce product quality over time (Goyal & Giri, 2001). Because these deterioration mechanisms directly affect inventory availability and product quality, PFSC inventory systems frequently incorporate age tracking, remaining shelf-life estimation First-In, First-Out (FIFO), First-Expired, First-Out (FEFO), Last-Stored, First-Out (LSFO), and Last-Expired, First-Out (LEFO), and issuing policies such as to minimize spoilage while maintaining service levels (Gulecyuz et al., 2025).

To address these complexities, the literature offers several methodological approaches for perishable inventory management. Early contributions primarily rely on deterministic models

that extend classical EOQ and lot-sizing formulations to account for product deterioration. Foundational studies (Covert & Philip, 1973; Ghare & Schrader, 1963), and the reviews by (Nahmias & Steven, 1982) demonstrate how deterioration rates, shelf-life limitations, and demand assumptions can be incorporated into replenishment decisions. More recent deterministic formulations embed perishability directly into production and inventory policies. For example, (Shin et al., 2019) incorporate shelf-life constraints into a two-phase inventory system, demonstrating how deterioration affects renewal and production decisions. Although deterministic models provide valuable analytical insights and establish important theoretical foundations, they often assume stable operating conditions and therefore may not fully capture the uncertainty observed in real PFSC environments.

When analytical formulations become too restrictive, researchers frequently employ simulation-based approaches to examine inventory behavior under realistic operating conditions. Discrete-event simulation (DES), agent-based modeling (ABM), and Monte Carlo simulation have been applied to evaluate inventory policies under fluctuating temperatures, uncertain arrival times, handling errors, and changing consumer demand patterns (Nikounam Nezami et al., 2024; Xue et al., 2019; Pol et al., 2024). For instance, (Gioia et al., 2023) incorporate consumer freshness preferences into inventory simulations to evaluate how age distributions evolve over time, while (Xu et al., 2020) utilize sensor-derived temperature data to analyze spoilage trajectories and assess replenishment strategies under different storage conditions. Such approaches provide valuable insights into operational behavior that is difficult to represent through closed-form optimization models alone.

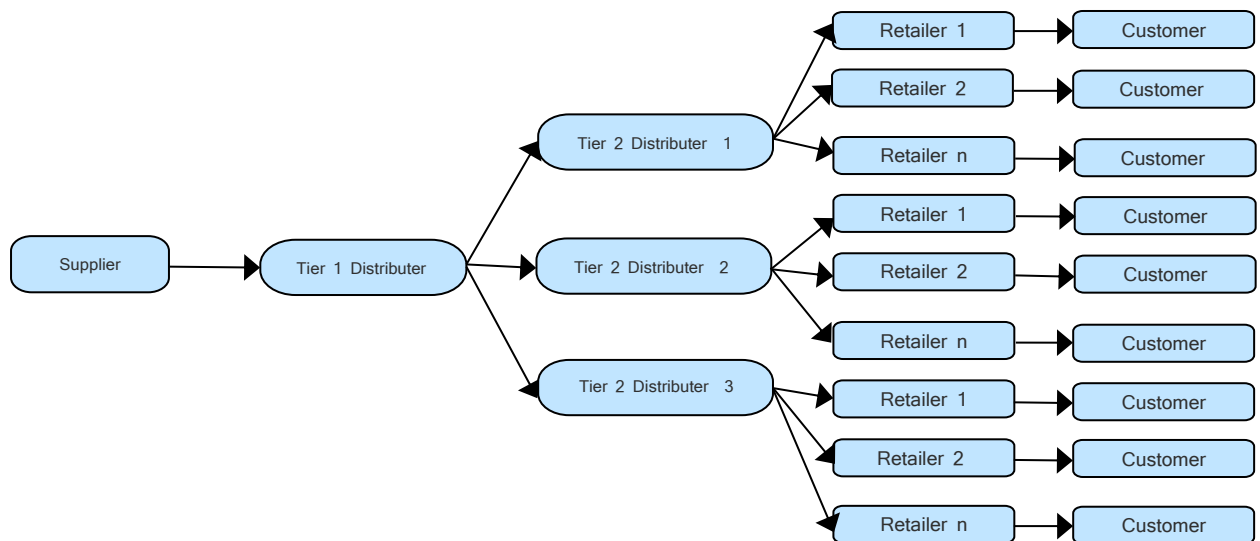


Figure 2.2 Multi-echelon inventory system of fresh products
Source: (Zhang et al., 2021)

In parallel, many studies apply heuristics and metaheuristics to address the computational complexity of large-scale perishable inventory problems. Genetic algorithms, particle swarm optimization, simulated annealing, tabu search, and hybrid solution procedures have been widely used in multi-product, multi-echelon, and integrated inventory systems (Alvarez et al., 2020; Pan et al., 2023), for example, develop a hybrid Branch-and-Cut and Iterated Local Search approach for the Perishable Inventory Routing Problem (PIRP), simultaneously considering spoilage constraints and routing decisions. Similarly, (Zhang et al., 2021) propose a centralized multi-echelon inventory framework that incorporates product deterioration and

optimizes replenishment decisions using a genetic algorithm. Their results demonstrate that coordinated inventory control can reduce both inventory costs and freshness losses across the supply chain.

Taken together, these methodological developments illustrate the progression of perishable inventory research from classical deterioration-aware replenishment models toward integrated and computationally sophisticated decision frameworks. The literature increasingly recognizes that inventory decisions are closely linked with procurement, production, and distribution activities, particularly when product quality evolves dynamically throughout the supply chain. As a result, recent research has shifted toward integrated approaches that jointly consider perishability, uncertainty, and cross-functional supply chain coordination.

2.5.2 Cold Food Supply Chain Management

Cold chain management represents a critical component of perishable food supply chains because product quality, safety, and remaining shelf life are highly dependent on maintaining appropriate temperature conditions throughout storage, handling, transportation, and distribution activities (Mustafa et al., 2024). The literature highlights several core characteristics that distinguish Cold Food Supply Chains (CFSCs) from ambient logistics systems.

First, temperature control is the defining requirement, as even brief deviations from prescribed thermal conditions can accelerate deterioration processes, reduce shelf life, and compromise food safety (Arriaga-Lorenzo et al., 2023). Maintaining thermal integrity requires specialized infrastructure and effective coordination among supply chain actors. Refrigerated warehouses, insulated packaging systems, and temperature-controlled vehicles form the physical foundation of CFSCs operations and are designed to minimize temperature excursions during storage and transportation (Shi et al., 2024). CFSCs are also inherently time-sensitive, given that perishable goods deteriorate continuously and require rapid handling to minimize biochemical and microbial changes (Tiwari & Tiwari, 2024). To maintain compliance with required thermal conditions, modern systems rely heavily on traceability and monitoring technologies, including RFID, IoT sensors, and data loggers, that provide real-time visibility of temperature, location, and handling conditions (Arriaga-Lorenzo et al., 2023; Mustafa et al., 2024).

CFSCs typically span several interconnected stages (as shown in figure 2.3), including procurement or harvest, processing and packaging, cold-storage, transportation, and distribution. The need to maintain strict thermal continuity across these stages makes coordination between actors, producers, distributors, carriers, and retailers, critically important (Mustafa et al., 2024). At the same time, these stringent requirements make cold chains cost-intensive and vulnerable to disruptions, as equipment failures, power outages, vehicle breakdowns, loading delays, or temperature excursions can lead to substantial product losses (Arriaga-Lorenzo et al., 2023). The combination of perishability, cost pressures, and operational complexity highlights why transportation planning is especially crucial: suboptimal routing or unnecessary delays directly reduce remaining shelf life and elevate the risk of spoilage. Consequently, efficient distribution and routing strategies play a central role in maintaining product quality, minimizing waste, and ensuring service levels in perishable supply chains, making cold chain logistics an important context for optimization models.

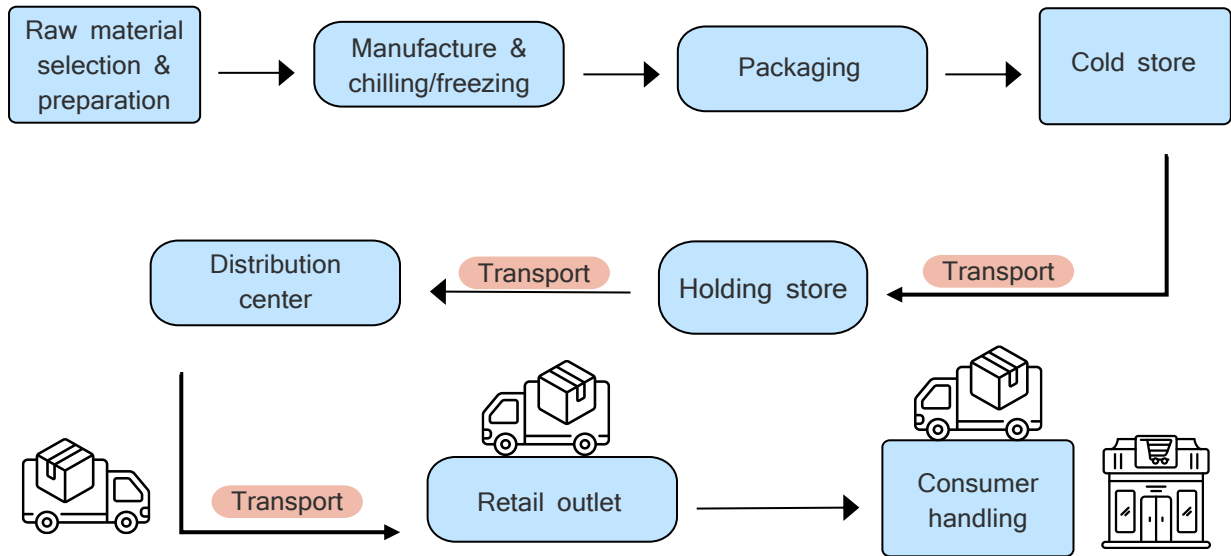


Figure 2.3 Block diagram representation of the cold chain process
Source: (Venkataraman et al., 2020)

Beyond operational decision making, the literature also emphasizes the strategic role of Supply Chain Network Design (SCND) in shaping CFSCs performance. SCND determines the configuration of facilities, capacities, and material flows required to maintain temperature-controlled operations throughout the supply chain (Accorsi et al., 2025). Facility location models are commonly used to identify suitable locations for refrigerated warehouses, cross-docking terminals, and distribution centers, thereby reducing transportation distances and limiting temperature-related quality losses (Ekşioğlu & Jin, 2006). Similarly, capacity-planning models determine appropriate cold-storage capacities and refrigerated fleet sizes to accommodate seasonal demand fluctuations while maintaining service levels (Osvald & Stirn, 2008). In geographically dispersed supply networks, hub-and-spoke configurations are frequently employed to consolidate flows of perishable products and improve operational efficiency (Shi et al., 2024).

2.6 Routing and Distribution in PFSC

2.6.1 Foundations of Routing in PFSCs

The routing of goods has long been recognized as one of the most fundamental problems in logistics, and the Vehicle Routing Problem (VRP) remains the foundation of most distribution-planning models. Originally introduced by (Dantzig & Ramser, 1959) through the well-known truck dispatching problem, the classical VRP seeks to determine vehicle routes that satisfy customer demand while minimizing transportation-related costs. Since its introduction, the VRP has evolved into a broad family of optimization models designed to accommodate increasingly complex operational requirements.

In conventional routing problems, transportation decisions primarily influence distribution efficiency and operational costs. In PFSCs, however, transportation duration and environmental conditions directly affect product quality, remaining shelf life, and food safety. Product deterioration continues throughout transportation and may accelerate when products

are exposed to unfavorable temperature conditions, making route selection a quality-preservation decision as well as a logistics decision (Ahmadi-Javid et al., 2023).

As a result, routing models for PFSCs extend beyond traditional cost-minimization objectives and increasingly incorporate perishability-related performance measures. The literature commonly identifies three major categories of routing objectives. The first focuses on economic performance, including transportation costs, travel distance, labor expenses, refrigeration energy consumption, and spoilage-related losses. The second emphasizes quality preservation, where routing decisions are evaluated according to remaining shelf life, freshness retention, food safety requirements, and customer satisfaction. The third reflects growing attention to sustainability considerations, including the reduction of CO₂ emissions, fuel consumption, and environmental impacts associated with transportation activities (Ahmadi-Javid et al., 2023; Alvarez et al., 2020; Awad et al., 2020; D. Li & Li, 2023)

Beyond these objectives, the incorporation of perishability fundamentally transforms the VRP from a static routing exercise into a time-temperature-quality optimization problem, where route feasibility and transportation performance are directly linked to the biochemical and microbial decay of transported products (Ahmadi-Javid et al., 2023).

2.6.2 Routing Models for Perishable Products

Recent reviews emphasize that perishability introduces a "biophysical clock" into routing because every additional minute in transit reduces remaining shelf life and narrows feasible delivery windows (Amorim & Almada-Lobo, 2014). To address these challenges, researchers have proposed several extensions of the classical VRP. Among them, the Vehicle Routing Problem with Time Windows (VRPTW) is one of the most widely adopted formulations in PFSC research. In VRPTW models, customers must be served within predefined delivery windows to maintain product quality and comply with food-safety requirements. Such constraints have become particularly important in the distribution of fresh meat, dairy products, and ready-to-eat foods, where even minor delivery delays may significantly increase spoilage and microbial-growth risks (Theophilus et al., 2021).

A second stream of research focuses on Perishable Vehicle Routing Problems (PVRP), which explicitly incorporate product deterioration into routing decisions. Unlike VRPTW models that primarily control delivery timing, PVRP formulations directly model freshness loss through deterioration functions, often exponential, temperature-dependent, or Arrhenius-based, embedded within the objective function or routing constraints. These models link route duration to product-quality outcomes and penalize freshness loss during transportation. Studies involving fresh vegetables, meat products, and other highly perishable foods demonstrate that transportation time and temperature exposure can significantly influence product value upon arrival, emphasizing that routing decisions cannot be evaluated purely on cost, as the "cheapest" route may lead to unacceptable quality degradation (Ahmadi-Javid et al., 2023).

Another important extension is the Time-Dependent Vehicle Routing Problem (TDVRP), which accounts for variations in travel speed resulting from congestion, weather conditions, and traffic patterns. In urban cold-chain environments, travel times may vary substantially throughout the day, creating additional uncertainty in product delivery. TDVRP formulations, therefore recognize that routing decisions involve not only selecting vehicle paths but also determining appropriate departure and travel times. Such models have become increasingly relevant for PFSCs because delays during peak traffic periods may prolong refrigeration

requirements, accelerate freshness deterioration, and increase spoilage risks (Awad et al., 2020).

Inventory and routing decisions are closely interconnected in PFSCs because replenishment timing directly influences inventory age, remaining shelf life, and delivery schedules. To capture these interactions, researchers extended the classical Vehicle Routing Problem toward the Inventory Routing Problem (IRP), in which inventory replenishment and transportation decisions are optimized simultaneously. (Coelho et al., 2014) developed a dynamic and stochastic IRP that incorporates random demand and travel-time information, demonstrating how real-time information can improve coordination between inventory and routing decisions in distribution systems. The integration of perishability considerations led to the development of the Perishable Inventory Routing Problem (PIRP), which explicitly incorporates product deterioration, age tracking, and shelf-life constraints into inventory-routing decisions. (Bertazzi et al., 2015) proposed a stochastic dynamic programming approach combined with a roll-out algorithm to evaluate replenishment policies under uncertainty. More recently, (Violi et al., 2020) introduced a mobile-horizon solution framework for uncertain cold-chain environments, while (Violi et al., 2023) developed risk-sensitive PIRP formulations that integrate stochastic demand, product-age dynamics, and risk-averse decision criteria. Their results show that dynamically updated inventory-routing policies can improve service levels and reduce spoilage, particularly when inventory age distributions are uncertain or only partially observable.

Although IRP and PIRP formulations represent an important step toward coordinated decision-making, they primarily focus on the interaction between inventory and distribution activities. Recent PFSC research therefore extends integration beyond inventory-routing coordination toward procurement, production, inventory, and routing decisions within a unified optimization framework, as discussed in the following section.

2.7 Integrated Approaches in Perishable Food Supply Chains

Integrated PFSC models emerged from the recognition that procurement, production, inventory, and distribution decisions cannot be treated as independent planning activities when products are subject to deterioration, limited shelf life, and strict delivery requirements. While early studies typically focused on a single operational function, researchers gradually observed that decisions made at one stage of the supply chain directly affect the feasibility and performance of subsequent stages. This realization motivated the development of integrated optimization models that simultaneously consider multiple decision layers within a unified framework.

The degree of integration has expanded considerably over time. Initial studies focused on coordinating production and distribution activities, whereas later contributions incorporated inventory management, facility-location decisions, supplier selection, sustainability objectives, and uncertainty considerations. As a result, integrated PFSC models have evolved from relatively narrow two-stage formulations into comprehensive multi-echelon frameworks capable of representing the complex interactions among procurement, production, inventory, and distribution decisions.

2.7.1 Foundations of Integrated Production-Distribution Planning

One of the earliest comprehensive reviews highlighting this research direction was conducted by (Ahumada & Villalobos, 2009), who examined planning models in agri-food supply chains and identified a growing interest in integrating production, inventory, transportation, and distribution decisions. Their review emphasized that perishability, quality deterioration, and limited shelf life require more holistic planning approaches than those commonly applied in traditional supply chains, motivating the development of integrated optimization models across multiple supply chain stages. Building upon this perspective, (H.-K. Chen et al., 2009) proposed a joint production-routing model under uncertain demand and delivery time-window constraints, solved through a hybrid Nelder-Mead and VRPTW heuristic. Their computational results demonstrated that misalignment between production completion and routing feasibility can result in substantial profit losses, highlighting the importance of coordinating production and distribution decisions.

A significant advancement was introduced by (Amorim et al., 2012), who developed a multi-objective framework for integrated production and distribution planning of perishable products. In addition to economic performance, the model explicitly incorporated product freshness while accounting for shelf life and spoilage. Their results showed that integrated planning outperforms decoupled approaches and that the benefits of integration depend strongly on the freshness level delivered to customers. (Li et al., 2016) developed an integrated MILP model that simultaneously considers production scheduling, inventory management, and vehicle routing with time windows for perishable products. A key feature of the model is the incorporation of a discrete quality index that tracks product deterioration throughout production and distribution activities, allowing freshness-dependent product value to be explicitly considered in decision-making. The study demonstrated that integrating production, inventory, and routing decisions improves coordination across supply chain stages while maintaining product quality and service performance. (Devapriya et al., 2017) expanded this line of research with a mixed-integer model and evolutionary metaheuristics that optimize production sequencing and delivery schedules under product-lifetime limits, demonstrating that integrated planning significantly reduces total costs and avoids infeasible delivery plans that arise under sequential decision-making.

As integrated formulations matured, researchers increasingly incorporated operational characteristics commonly observed in real-world food supply chains, (Lacomme et al., 2018) investigated an integrated production and transportation scheduling problem for perishable products distributed by multiple vehicles. Their model jointly coordinates production schedules and transportation activities while considering vehicle capacity limitations and product shelf-life constraints. The objective was to minimize the overall makespan of deliveries. To solve the problem, the authors developed a hybrid Greedy Randomized Adaptive Search Procedure combined with Evolutionary Local Search (GRASP $\times$ ELS). Computational experiments showed that the proposed algorithm outperformed existing approaches and produced high-quality solutions for newly introduced multi-vehicle benchmark instances. The study contributed by extending integrated production-transportation planning from single-vehicle settings to more realistic multi-vehicle environments while explicitly accounting for perishability. (Qiu et al., 2019) advanced the integration by modeling a multi-period framework that jointly optimizes lot-based inventory, periodic production, and delivery assignments over time, using a branch-and-cut algorithm to enforce perishability-aware replenishment and sales policies. The formulation incorporates perishability-aware replenishment and sales policies and was solved using a branch-and-cut algorithm. The results demonstrated the benefits of

coordinating inventory, production, and distribution decisions within a unified planning framework for perishable products. (Liu & Liu, 2020) focused on integrating single-machine production sequencing with multi-vehicle delivery routing, formulating a weighted delivery-time minimization model to coordinate service priorities across the PFSC, and solving it with a large neighborhood search metaheuristic.

Collectively, these studies demonstrate a clear progression in the literature, from recognizing the need for coordination across supply chain stages to developing increasingly comprehensive frameworks that jointly optimize procurement, production, and distribution decisions while accounting for perishability and product quality considerations.

2.7.2 Strategic and Multi-Stage Integration in PFSCs

As integrated PFSC models evolved, researchers increasingly extended the scope of coordination beyond production and distribution decisions to include strategic and multi-stage planning activities, such as facility location, procurement, inventory positioning, and transportation management. (Govindan et al., 2014), who developed a two-echelon location-routing model for sustainable perishable food supply chains. Their framework simultaneously optimized facility locations, product flows, and vehicle routes while incorporating both economic and environmental objectives. To solve the resulting complex problem, the authors employed a hybrid metaheuristic combining multi-objective particle swarm optimization and adaptive variable neighborhood search. The study demonstrated that sustainability considerations, particularly greenhouse gas emissions and carbon footprint reduction, can be effectively incorporated into strategic network design decisions. (Vahdani et al., 2017) further expanded integration by developing a production-inventory-routing coordination model for perishable products that jointly optimizes production scheduling, inventory management, and vehicle routing under capacity and time-window constraints. The model considers a multi-stage, multi-site, and multi-period production system together with heterogeneous transportation vehicles and stochastic customer demand. The objective was to maximize expected profit while accounting for transportation, inventory, and shortage costs. Due to the complexity of the formulation, the authors proposed both heuristic and metaheuristic solution approaches. Computational results showed that the metaheuristic method consistently generated superior solutions, highlighting the value of integrated decision-making in complex perishable supply chains.

The integration framework was extended further by (Rafie-Majd et al., 2018), who incorporated inventory management decisions under stochastic demand conditions. Their multi-period inventory-location-routing model jointly determines distribution center locations, inventory policies, and vehicle routing plans while accounting for multiple perishable products, heterogeneous transportation fleets, waste generation, and shelf-life limitations. Given the complexity of the resulting Mixed-Integer Nonlinear Programming (MINLP) formulation, the authors proposed a Lagrangian relaxation approach combined with a heuristic feasibility procedure. Computational results confirmed that simultaneously optimizing location, inventory, and routing decisions can substantially improve supply chain performance compared with sequential planning approaches.

The literature reveals a clear shift from logistics-oriented integration toward broader network-level coordination across multiple supply chain echelons. As integrated models became more sophisticated, the focus expanded from location-routing decisions to the simultaneous optimization of inventory policies, sourcing strategies, replenishment decisions, and

transportation activities under uncertainty. These developments established the foundation for contemporary PFSC frameworks that seek to coordinate strategic, tactical, and operational decisions within a single optimization structure.

Research has further expanded the integration boundary to include upstream procurement decisions. For example, (G. Wang, 2021) proposed an integrated procurement-production-distribution scheduling model for an e-commerce supply chain, formulated as a mixed-integer nonlinear programming problem that simultaneously determines supplier selection, procurement quantities, production schedules, and retailer assignments. By incorporating nonlinear penalty costs associated with unmet demand and spillover effects, the study illustrated how procurement decisions can directly influence downstream production and distribution performance. To address the resulting computational complexity, a hybrid Augmented Lagrangian-Particle Swarm Optimization algorithm was developed for solving the non-convex model efficiently.

2.7.3 Comprehensive PIRP and Resilient PFSC Frameworks

As integrated PIRP formulations matured, researchers increasingly incorporated sustainability objectives, environmental considerations, and multiple sources of uncertainty into a unified decision-making framework. (Chan et al., 2020) presented a four-objective model that integrates production, inventory, routing, and environmental concerns by capturing trade-offs among cost, freshness, emissions, and lead time, solved using a custom multi-objective particle swarm optimization method. (Ghasemkhani et al., 2022) proposed an integrated production-inventory-routing model for multi-perishable products under uncertainty. Their mixed-integer linear programming formulation simultaneously optimizes production, inventory, and distribution decisions while considering heterogeneous vehicles, time windows, and fuzzy demand uncertainty. To solve large-scale instances, the authors developed Hybrid Imperialist Competitive Algorithm (HICA) and Self-Adaptive Differential Evolution (SADE) metaheuristics, with computational results demonstrating the superior performance of HICA (Sun et al., 2023). The study proposes an integrated production-inventory-routing model for multiple perishable products, jointly optimizing production, inventory, and transportation decisions. Two models are developed to minimize either total costs or carbon emissions while incorporating product deterioration and shelf-life constraints. A particle swarm optimization (PSO) algorithm is used to solve the problem, and computational results demonstrate the trade-offs between economic and environmental objectives.

Recent research has increasingly focused on resilience and stochastic deterioration, motivated by the COVID-19 pandemic, which revealed the vulnerability of integrated supply chains to disruptions affecting supplier reliability, production timing, and distribution capacity. (Hashemi-Amiri et al., 2023) developed one of the most advanced formulations in this stream, a distributionally robust integrated supplier-production-routing model that jointly optimizes sourcing decisions, production schedules, and vehicle routing under ambiguous and highly variable demand. Their results show that coordinated and robust decisions significantly reduce shortages and unmet demand compared to sequential planning. A related contribution by (Yazdekhaei et al., 2021) proposes a multi-period, multi-modal stochastic PFSC model for the poultry industry, integrating supplier selection, replenishment, and transportation-mode routing. Their hybrid branch-and-cut and dynamic programming method demonstrates that jointly adapting sourcing and modal routing improves resilience against pandemic-induced demand and transport uncertainties. Complementing these quantitative works, (Moosavi et al., 2022) provide a broad analytical assessment of COVID-19 supply chain disruptions,

highlighting the strategic importance of integrated decisions, such as multi-sourcing, flexible transportation, and decentralized inventories, for building resilience in perishable food systems. (Komijani & Sheikh Sajadieh, 2024) moves beyond traditional PIRP formulations by explicitly modelling stochastic product lifespans. Their scenario-based MILP captures the inherent uncertainty of biological decay and integrates production planning, age-dependent inventory decisions, and routing under freshness constraints within a single framework. The model also incorporates closed-loop dynamics, allowing spoiled returns to be converted into raw materials, and embeds supplier-side order splitting to hedge against lifespan variability. Using a hybrid PSO-SA metaheuristic, the authors demonstrate that assuming a fixed lifespan, as many earlier studies do, can misestimate system costs by up to 25 percent, underscoring the value of biologically realistic, uncertainty-aware integration. By linking stochastic deterioration to procurement, production, inventory ageing, and routing decisions, this study represents a significant step forward in the development of comprehensive PFSC models.

Taken together, these studies demonstrate that integrated PFSC research has evolved from coordinating production, inventory, and distribution decisions toward uncertainty-aware frameworks that simultaneously address sustainability, resilience, and stochastic deterioration. Contemporary models increasingly seek to capture the biological and operational realities of perishable supply chains while maintaining coordination across multiple decision layers.

2.7.4 Research Gaps and Limitations in Existing Integrated PFSC Models

Although integrated PFSC models have advanced considerably over the past two decades, several important limitations remain. A recurring observation throughout the literature is that increasing model sophistication has not always been accompanied by a corresponding increase in supply chain realism. While recent studies have expanded the scope of integration to include production, inventory, routing, sustainability, and uncertainty considerations, many practical characteristics of real-world perishable food systems remain insufficiently represented.

One of the most prominent limitations concerns the structural scope of existing models. A large proportion of integrated PFSC studies focus on coordinating two decision layers, such as production-distribution, inventory-routing, or location-routing decisions. These formulations have demonstrated the benefits of coordination between adjacent supply chain stages; however, truly end-to-end integration remains relatively uncommon. In particular, procurement, production, inventory aging, warehousing, and retailer-level distribution are often modeled separately or only partially connected. Consequently, many operational interdependencies observed in practice, such as the influence of procurement timing on production schedules, inventory freshness, and downstream routing feasibility, remain inadequately captured.

Another important limitation is the limited treatment of cold-storage operations. Despite the central role of temperature-controlled warehousing in preserving product quality and extending shelf life, most integrated PFSC models assume simplified storage conditions, instantaneous dispatch, or unrestricted warehouse capacity. Explicit modeling of storage duration, refrigeration capacity, temperature-dependent deterioration, and warehouse-level operational constraints remains rare. More importantly, the interaction between cold-storage, production scheduling, inventory aging, and transportation decisions is largely overlooked. As a result, many existing formulations do not fully reflect the operational realities of refrigerated food supply chains.

The literature also reveals a persistent gap between theoretical models and industrial practice. Most integrated PFSC studies rely on synthetic datasets, benchmark instances, or stylized numerical experiments. Empirical applications involving real food manufacturers, particularly SMEs, remain comparatively scarce. This limitation is significant because SMEs often operate under resource constraints, limited planning capabilities, heterogeneous customer networks, and restricted transportation fleets that differ substantially from the assumptions commonly adopted in academic models. The limited availability of real-world validation therefore raises questions regarding the scalability, implementability, and practical applicability of many existing formulations.

Beyond operational integration, several studies have begun incorporating sustainability and resilience considerations into PFSC decision-making. However, these dimensions are frequently treated as supplementary objectives rather than being embedded directly within the underlying system structure. Environmental indicators such as carbon emissions, waste generation, and resource utilization are often evaluated as additional performance measures rather than integrated into the operational logic governing procurement, production, inventory, and routing decisions. Similarly, resilience-related factors, including demand volatility, transportation disruptions, and supply uncertainty, are typically examined in isolation and only rarely combined with explicit perishability dynamics and inventory aging processes.

Among the studies reviewed, the distributionally robust framework proposed by (Hashemi-Amiri et al., 2023) represents one of the most comprehensive attempts to address uncertainty within an integrated PFSC setting. By jointly optimizing supplier selection, production scheduling, and vehicle routing under ambiguous demand conditions, the model demonstrates the value of coordinated and robust decision-making. Although the model significantly advances uncertainty-aware integration, it does not fully capture several operational features commonly observed in real perishable food supply chains. The framework retains a three-echelon structure and does not explicitly incorporate warehouse-level cold-storage operations, multi-period inventory aging across the network, or retailer-level replenishment planning. Furthermore, the model is not calibrated to SMEs-scale food production systems or validated using real industrial data.

Taken together, these limitations highlight a clear opportunity for further research. Existing integrated PFSC models have made substantial progress in coordinating selected supply chain decisions, yet few simultaneously capture multi-echelon interactions, perishability dynamics, cold-storage operations, routing decisions, and real-world operational constraints within a unified framework. The present study seeks to address these gaps by developing an integrated optimization model that combines procurement, production, cold-storage inventory management, distribution planning, and vehicle routing using data obtained from an SMEs-scale food manufacturer. In doing so, it aims to contribute a more operationally realistic representation of perishable food supply chain decision-making.

Table 2.1 Research gap

Reference	Decision	Product	Mathematical Formulation										Implementation	Uncertainty					Perishability representation		Fleet	Solution method							
			Objectives																										
			Facility location	Supplier selection	Production scheduling	Inventory management	Routing	Single	Multi	Single-Objective	Multi-Objective	Economic		Quality & Freshness	Supplier reliability	Service Level Objectives	Sustainability	Case study	Numerical example	Deterministic			Stochastic	Robust	Distributionally robust	Fuzzy	Time window	Constant deterioration rate	Discrete quality levels
(Eksioglu & Jin, 2006)			✓	✓		✓		✓		✓						✓	✓									✓			Primal-dual heuristic for large instances; exact MILP for small cases
(Govindan et al., 2014)	✓				✓	✓			✓	✓				✓		✓	✓						✓		✓		✓		Hybrid MOPSO-AMOVNS (MHPV) for solving bi-objective LRP with time windows
(Li et al., 2016)			✓	✓	✓			✓		✓						✓	✓								✓		✓		Exact MILP solved with CPLEX and strengthened valid inequalities
(Devapriya et al., 2017)			✓		✓	✓		✓		✓						✓	✓									✓	✓		MILP with evolutionary metaheuristics for large-scale scheduling-routing
(Vahdani et al., 2017)			✓	✓	✓		✓	✓		✓						✓		✓					✓	✓			✓		hybrid exact + heuristic + metaheuristic
(Qiu et al., 2019)			✓	✓	✓	✓		✓		✓				✓		✓	✓							✓			✓		Branch-and-cut MILP for multi-period production-inventory-routing
(Chan et al., 2020)			✓	✓	✓	✓			✓	✓	✓			✓	✓	✓	✓								✓		✓		Multi-objective PSO (MO-GLNPSO) for four-objective PIRP
(Xu et al., 2020)				✓	✓	✓		✓		✓				✓			✓						✓	✓			✓		Exact MILP solved by CPLEX, simulation-driven hybrid
(L. Liu & Liu, 2020)			✓		✓	✓		✓					✓			✓	✓										✓		Exact CPLEX for small cases + ILNS metaheuristic for larger instances
(Yazdekhaei et al., 2021)	✓		✓	✓	✓	✓		✓		✓				✓				✓									✓		Hybrid (exHybrid branch-and-cut + dynamic programming (BBDP)act + metaheuristic)
(A. Liu et al., 2021)	✓			✓	✓	✓			✓	✓	✓			✓		✓	✓							✓			✓		Exact (MILP) + Weighted Multi-objective Method
(Ghasemkhani et al., 2022)			✓	✓	✓		✓	✓		✓				✓	✓						✓	✓		✓			✓		Fuzzy MILP solved with hybrid ICA-SADE metaheuristic
(Majidi et al., 2022)			✓	✓	✓		✓		✓	✓				✓	✓		✓									✓	✓		Exact method: ε -constraint method (only for small instances), Metaheuristic: Fuzzy Domination Self-Learning NSGA-II (FDSL-NSGA-II), an enhanced NSGA-II
(Pratap et al., 2022)			✓	✓	✓		✓	✓		✓						✓		✓					✓	✓			✓		Metaheuristic solution (CSA and FPA)
(Sun et al., 2023)			✓	✓	✓		✓		✓	✓	✓			✓		✓	✓								✓		✓		CPLEX (exact MINLP solving), PSO-based metaheuristic
(Hashemi-Amiri et al., 2023)		✓	✓		✓	✓			✓	✓		✓			✓					✓		✓	✓				✓		The DRO-MILP is solved using Gurobi for small sizes
(Mostaghim et al., 2024)		✓	✓	✓	✓		✓		✓	✓				✓	✓			✓	✓					✓			✓		GAMS + CPLEX to solve the MILP (exact method), + robust + stochastic methodology
(Komijani & Sheikh Sajadieh, 2024)		✓	✓	✓	✓		✓	✓		✓						✓		✓								✓	✓		PSO-SA hybrid algorithm (PSOSA)
(Mostaghim et al., 2024)	✓	✓		✓			✓		✓	✓				✓	✓			✓						✓					MILP solved via GAMS-CPLEX with stochastic and robust extensions
(G. Wang, 2024)		✓	✓			✓		✓		✓						✓	✓							✓					Hybrid: exact algorithms + heuristic + CPLEX comparison
This Study		✓	✓	✓	✓	✓		✓		✓				✓	✓					✓		✓	✓			✓			Exact method (MILP solved using Gurobi) with ε -constraint method for multi-objective optimization

3. Methodology

3.1 Overview of the Base Model and Motivation for Extension

This thesis builds upon “Integrated supplier selection, scheduling, and routing problem for perishable product supply chain: A distributionally robust approach” proposed by (Hashemi-Amiri et al., 2023), which serves as the methodological foundation for the extensions developed in this study. The optimization framework provides an integrated approach for modeling perishable food supply chains under uncertainty. Their model considers a three-echelon structure composed of suppliers, a manufacturer, and retailers, where decisions related to supplier selection, production scheduling, and vehicle routing are optimized simultaneously. Supplier selection is modeled through binary activation variables that determine which suppliers are used for procurement, incorporating reliability scores, procurement prices, and inbound transportation costs. Production scheduling is formulated on a single production line, where products are processed sequentially, and setup and processing times are explicitly represented. The timing of production directly influences routing decisions, because each vehicle departs immediately after the completion of its assigned production batch. Distribution planning is represented as a heterogeneous capacitated VRPTW, where each retailer must be served within a predefined time window, and early or late arrivals result in inventory or goodwill-loss penalties. A key methodological feature of the base model is the use of DRCCs, which model demand uncertainty through moment-based ambiguity sets characterized by empirical means and covariances; these constraints ensure that decisions remain feasible for all probability distributions consistent with the available statistical information. The authors validate their model using a detailed poultry supply chain case study and demonstrate that the integrated framework effectively identifies optimal supplier portfolios, production plans, and routing schedules under uncertainty. Furthermore, the authors perform sensitivity analyses on core parameters (e.g., demand variance, deterioration rates, and DRCC confidence levels) to assess the stability and practical robustness of their model under varying operational conditions.

This thesis adopts the Hashemi-Amiri model as its foundation because it offers:

- (i) a **strong methodological basis** grounded in modern optimization techniques,
- (ii) an **integrated treatment** of procurement, production, and routing decisions,
- (iii) a **DRCC structure** that robustly incorporates uncertainty, and
- (iv) a **modeling framework well aligned with the operational characteristics** of perishable supply chains.

Although the Hashemi-Amiri framework is rigorous, it includes simplifying assumptions that limit its applicability to real-world food manufacturing contexts. The most significant gaps include:

- (1) **the absence of finished-goods cold-storage**, which in practice is essential for chilling, staging, buffering, and aligning production with delivery schedules;
- (2) **the assumption of a single raw material per product**, which prevents modeling multi-ingredient production and BOM;
- (3) **binary supplier selection** rather than multi-supplier allocation through continuous procurement quantities subject to material-specific capacities;
- (4) **the absence of a sustainability** or CO₂-emission objective;

- (5) **the restrictive link between production completion and immediate vehicle departure**, eliminating realistic buffering; and
- (6) **a simplified perishability model** that does not include deterioration during storage.

Building on these limitations, this thesis develops an extended, multi-period PFSC model tailored to the operational realities of a mid-sized Mongolian ready-to-eat meal manufacturer. Although the (Hashemi-Amiri et al., 2023) model provides a rigorous optimization framework, its simplifying assumptions restrict its ability to represent key operational characteristics commonly encountered in practical food manufacturing environments, including multi-ingredient production, temporary cold-storage of finished products, flexible procurement from multiple suppliers, and sustainability-oriented decision-making. To address these limitations, the proposed EIPAPRP incorporates multi-material procurement based on BOM, aggregate production planning, explicit cold-storage dynamics with deterioration, distributionally robust demand modeling, and a transportation-related CO₂-emission objective. These extensions provide a more realistic representation of perishable food supply chain operations while maintaining a computationally tractable mixed-integer linear programming framework.

3.2 Problem Description of the Extended Model

The extended system consists of multiple raw-material suppliers, a single manufacturer operating an aggregated production facility, a centralized cold-storage depot, and a network of retailers with strictly regulated delivery time windows. The resulting planning problem integrates procurement, production planning, inventory dynamics, and VRPTW decisions into a unified optimization framework capable of addressing perishability, demand uncertainty, and sustainability requirements through a DRO framework.

The planning horizon is divided into discrete periods. At the start of each period, the manufacturer procures several distinct raw materials from a set of suppliers. Unlike the base model, which assumes a single input material, each finished product in the proposed system requires multiple ingredients defined through a BOM. Procurement decisions therefore consider supplier capacities, material availability, purchasing costs, and inbound transportation costs. Raw materials may be stored in inventory and carried across planning periods, allowing production decisions to utilize both newly procured materials and inventories accumulated from previous periods. This creates a temporal link between procurement and production through the raw-material inventory balance. Supplier allocation is determined endogenously through the procurement quantity variables; suppliers receiving positive procurement quantities are considered active in the corresponding planning period.

Production is performed on an aggregated facility rather than a sequenced single-line system, reflecting the operational practices of many SMEs food manufacturers where production capacity is measured in aggregate units. Finished-goods produced in each period are transferred into a refrigerated storage depot. Unlike the base model, where products are delivered immediately after production, the proposed model introduces a cold-storage stage that allows temporary storage of finished-goods before distribution. The cold-storage capacity constraint applies only to finished-goods inventory held at the depot. Raw materials are assumed to be stored at the production facility and are therefore modeled separately through raw-material inventory balance equations and raw-material inventory holding costs. This assumption reflects the operational separation between production-side material storage and finished-goods staging prior to distribution. Together with the explicit modeling of raw-material procurement and inventory dynamics, this creates a more realistic representation of the supply chain flow.

Inventory dynamics in cold-storage are modeled using a first-order multiplicative deterioration factor, whereby a constant fraction of finished-goods inventory deteriorates in each period. This formulation captures the essential effect of perishability while preserving linearity and avoiding the computational complexity associated with age-indexed shelf-life tracking.

Consistent with the base model, uncertainty is addressed using a DRO framework, which seeks solutions that remain feasible across a family of probability distributions characterized by empirical demand moments. Retailer demand is uncertain and represented through empirical means and standard deviations estimated from historical data. To ensure that service plans remain feasible under demand variability, the model applies a distributionally robust demand-satisfaction constraint. Delivered quantities must exceed the empirical mean demand plus a safety margin proportional to the standard deviation, ensuring a service reliability level of $1 - \varepsilon$ under incomplete distributional information.

The distribution stage is formulated as a Vehicle Routing Problem with Time Windows (VRPTW). Retailers specify allowable service intervals. Unlike the base model, which treats early arrivals as time-window violations associated with inventory-cost penalties and does not explicitly model vehicle waiting, the proposed formulation allows vehicles to arrive before the opening of a retailer's time window and wait until service can begin.

Late service remains possible but incurs a goodwill-loss penalty. Routing decisions must satisfy vehicle capacity constraints, time-window restrictions, depot departure and return requirements, and subtour elimination through Miller-Tucker-Zemlin (MTZ) constraints.

The integrated PFSC model simultaneously determines procurement quantities of raw materials from suppliers, production quantities of finished products in each period, cold-storage inventory levels subject to deterioration, and vehicle routing plans including delivery quantities, service-start times, waiting durations, and lateness penalties.

Two conflicting performance dimensions are considered. The first is total economic cost, including procurement, inbound transportation, production, cold-storage holding costs, routing costs, and penalties for late deliveries. The second objective measures environmental impact through CO₂ emissions generated by vehicle travel. To analyze the trade-off between economic and environmental performance, the model applies the ε -constraint method, in which total cost is minimized while emissions are restricted by a parameterized upper bound. By varying the ε parameter, multiple Pareto-efficient solutions are generated, allowing decision-makers to evaluate different cost-emission trade-offs.

Research Contribution

This thesis extends the base (Hashemi-Amiri et al., 2023) model by replacing the single-input procurement structure with multi-supplier allocation and raw-material procurement decisions based on BOM. The model further introduces raw-material and finished-goods inventory dynamics, a cold-storage stage that decouples production from distribution, and a VRPTW formulation that explicitly captures delivery scheduling decisions. Demand uncertainty continues to be handled through a DRO framework, while transportation-related CO₂ emissions are incorporated through an ε -constraint approach to evaluate economic-environmental trade-offs.

These extensions provide a more realistic representation of perishable food production and distribution systems with cold-storage operations while maintaining computational tractability.

3.3 Mathematical formulation of the extended model

Table 3.1 Sets & Indices

Sets & Indices	Description
Q	Set of suppliers, indexed by q
R	Set of raw materials, indexed by r
N	Set of finished products, indexed by n
I	Set of retailers (customers), indexed by i
V	Routing nodes, $V = \{0\} \cup I$, where 0 is the depot (cold-storage)
K	Set of vehicles, indexed by k (vehicles homogeneous)
T	Set of planning periods indexed by t . Each period represents one working day, with $t = 1$ denoting the first period of the horizon. Within each day, continuous time is measured in minutes past midnight, and is used for routing and service-time variables (arrival, service start, waiting, lateness)

Table 3.2 Parameters

Parameters	Description	Units
Procurement & BOM		
$PC_{q,r}$	Purchase price of raw material r from supplier q	¥/unit
$TC_{q,r}$	Inbound transport cost per unit from supplier q for material r	¥/unit
$Avail_{q,r}$	1 if supplier (q) offers raw material (r); 0 otherwise.	binary
$Cap_{q,r}^{sup}$	Capacity of supplier q to supply material r	units
$b_{r,n}$	BOM coefficient, units of raw material r needed per unit of product n (raw units per finished unit)	units/unit
Production & Storage		
c_n^{prod}	Production unit cost for product n	¥/unit
Cap^{prod}	Aggregated production capacity per period	units/period
h_n	Cold-storage holding cost for product n at depot per period	¥/unit-period
$h_{mat,r}$	Holding cost for raw material r per period	¥/unit-period
	Storage deterioration fraction per period for product n	fraction
Cap^{stor}	Cold-storage capacity	units
Routing & time		
$Tr_{i,j}$	Travel time from node i to j	minutes
$Dist_{i,j}$	Travel distance between node i and j	km
s_i	Service duration at retailer i	minutes
s_0	Service duration at the depot (no service is performed at the depot)	minutes
ER_i	Earliest allowable service-start time at retailer i	minutes past midnight
LT_i	Latest allowable service-start time at retailer i	minutes past midnight
T^{max}	Upper bound on routing time variables within a day	minutes past midnight
C	Vehicle capacity (kg)	kg
w_n	Weight of product (n) per unit	kg/unit
Cost & emissions		
FC	Fixed cost per vehicle per route used	¥
VC	Variable travel cost parameter	¥/km
e	Vehicle emission factor	kg CO ₂ /km

Table 3.2 (Continued)

Parameters	Description	Units
Service & penalty		
GL	Lateness (goodwill) penalty	£/minute
Demand uncertainty & DRO risk tolerance parameter		
$\mu_{i,n,t}$	Mean demand (units) of product n at retailer i in period t	units
$\sigma_{i,n,t}$	Standard deviation of demand (units) of product n at retailer i in period t	units
ε_{DRO}	DRO risk tolerance level	-
U_{max}	Upper bound for MTZ ordering variable	-
$M_{i,j,t}$	Big-M constant for time propagation: $M_{i,j,t} = T^{\max}$.	minutes
$U_{i,n,t}^{\delta}$	Demand-based upper bound on delivered quantity of product n to retailer i in period t	units

VC represents the variable transportation cost per kilometer traveled. Accordingly, the routing cost component is calculated using the travel distance between nodes. The CO₂ emission factor e is also expressed per kilometer traveled, ensuring consistency between the economic and environmental objectives, both of which depend on transportation distance.

$U_{i,n,t}^{\delta}$ used as data-driven Big-M upper bound used in the routing-delivery linking constraints in the routing-delivery linking constraints, defined as:

$$U_{i,n,t}^{\delta} = \mu_{i,n,t} + \sqrt{\frac{1 - \varepsilon_{DRO}}{\varepsilon_{DRO}}} \sigma_{i,n,t}$$

Table 3.3 Decision Variables

Decision Variables	Description
$Mat_{q,r,t} \geq 0$	Quantity of raw material r purchased from supplier q in period t
$MatInv_{r,t} \geq 0$	End-of-period inventory level of raw material r at the production facility in period t
$y_{n,t} \geq 0$	Quantity of product n produced in period t
$I_{n,t} \geq 0$	End-of-period inventory of finished product n in cold-storage
$\delta_{k,i,n,t} \geq 0$	Quantity of product n delivered by vehicle k to retailer i in period t
$ArT_{i,t} \geq 0$	Arrival time of the vehicle at retailer i in period t
$Start_{i,t} \geq 0$	Service start time at retailer i in period t (minutes), defined as: $Start_{i,t} = \max\{ArT_{i,t}, ER_i\}$
$Wait_{i,t} \geq 0$	Waiting time at retailer i , defined as: $Wait_{i,t} = Start_{i,t} - ArT_{i,t}$
$L_{i,t} \geq 0$	Lateness at retailer i in period t , defined as: $L_{i,t} = \max\{Start_{i,t} - LT_i, 0\}$
$u_{i,k,t}$	MTZ ordering variable (bounded in $[1, U_{max}]$) $U_{0,k,t} = 0 \quad \forall k \in K, t \in T$
Binary / Integer Variables	
$X_{i,j,k,t} \in \{0, 1\}$	1 if vehicle k travels directly from node i to node j in period t ; 0 otherwise
$V_{k,t} \in \{0, 1\}$	1 if vehicle k is activated in period t ; 0 otherwise

3.3.1 Objective Function

Monetary Cost Objective

$$\begin{aligned}
 Z_{\text{cost}} = & \sum_{t \in T} \sum_{q \in Q} \sum_{r \in R} PC_{q,r} \text{Mat}_{q,r,t} \\
 & + \sum_{t \in T} \sum_{n \in N} c_n^{\text{prod}} y_{n,t} \\
 & + \sum_{t \in T} \sum_{n \in N} h_n I_{n,t} \\
 & + \sum_{t \in T} \sum_{r \in R} h_{\text{mat},r} \text{MatInv}_{r,t} \\
 & + \sum_{t \in T} \sum_{k \in K} FC V_{k,t} \\
 & + \sum_{t \in T} \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} VC \text{Dist}_{i,j} X_{i,j,k,t} \\
 & + GL \sum_{t \in T} \sum_{i \in I} L_{i,t} \\
 & + \sum_{t \in T} \sum_{q \in Q} \sum_{r \in R} TC_{q,r} \text{Mat}_{q,r,t}
 \end{aligned} \tag{Obj-Cost}$$

$$Z_{\text{CO2}} = \sum_{t \in T} \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} e \cdot \text{Dist}_{i,j} X_{i,j,k,t} \tag{Obj-CO2}$$

3.3.2 Constraints

Procurement constraints

$$\text{Mat}_{q,r,t} \leq \text{Avail}_{q,r} \text{Cap}_{q,r}^{\text{sup}} \quad \forall q \in Q, r \in R, t \in T \tag{C1}$$

(C1) ensures that supplier q is only allowed to provide raw material r if it is available ($\text{Avail}_{q,r} = 1$), and limits procurement by the supplier's material-specific production capacity $\text{Cap}_{q,r}^{\text{sup}}$. This prevents infeasible procurement plans that exceed realistic supply limits.

$$\text{MatInv}_{r,1} = \text{MatInv}_r^0 + \sum_{q \in Q} \text{Mat}_{q,r,1} - \sum_{n \in N} b_{r,n} y_{n,1} \quad \forall r \in R \tag{C2}$$

$$MatInv_{r,t} = MatInv_{r,t-1} + \sum_{q \in Q} Mat_{q,r,t} - \sum_{n \in N} b_{r,n} y_{n,t} \quad \forall r \in R, \quad t = 2, \dots, |T|$$

(C2) The raw material inventory balance constraint ensures material flow conservation over the planning horizon. For each raw material and time period, the ending inventory equals the inventory from the previous period plus incoming deliveries from suppliers, minus the raw material consumed in production. Consumption is determined by the BOM coefficients and the corresponding production quantities. In the first period, the initial inventory replaces the previous-period inventory. This constraint guarantees that production decisions remain consistent with raw material availability in each period.

$$y_{n,t_0} = 0 \quad \forall n \in N, \quad (C3)$$

(C3) prevents production during the initialization period t_0 , which is reserved for procurement activities and the establishment of initial raw-material inventory levels prior to the start of production planning.

Production Constraints

$$\sum_{n \in N} y_{n,t} \leq Cap^{prod} \quad \forall t \in T, \quad t \neq t_0 \quad (C4)$$

(C4) The aggregated production capacity constraint limits the total production volume across all finished products. The model assumes a common capacity unit and therefore treats all finished-product quantities as consuming the same production-capacity resource. This reflects the operational reality of a single (aggregated) production facility where only a limited total throughput can be processed per period regardless of product mix. It preserves linearity and keeps the scheduling model tractable by avoiding line-level sequencing while still constraining total output.

Unlike (Hashemi-Amiri et al., 2023), the extended model in this thesis does not include detailed production sequencing or machine-level scheduling. This is intentional and reflects the operational reality of the case-study manufacturer, where finished-goods are produced in daily batches using multiple parallel equipment units and do not require single-machine sequencing. Instead, production is modeled through aggregated capacity constraints and BOM feasibility, which substantially simplifies computational complexity while remaining consistent with real factory operations. This allows the model to focus on the procurement, inventory, cold-storage, and distribution layers under uncertainty without introducing unnecessary scheduling complexity.

$$I_{n,t} = (1 - \beta_n) I_{n,t-1} + y_{n,t} - \sum_{k \in K} \sum_{i \in I} \delta_{k,i,n,t} \quad \forall n \in N, \quad t \in T \quad (C5)$$

$$I_{n,0} = 0 \quad \forall n \in N \quad (C6)$$

$$\sum_{k \in K} \delta_{k,i,n,t} \leq (1 - \beta_n) \cdot I_{n,t-1} + y_{n,t} \quad \forall n \in N, t \in T \quad (C7)$$

(C5) models inventory dynamics in the cold-storage depot using a first-order multiplicative decay factor β_n per period. The beginning-of-period inventory $I_{n,t-1}$ ages and loses a fraction β_n of its usable quantity; the surviving fraction $(1 - \beta_n)I_{n,t-1}$ is carried forward. Production $y_{n,t}$ enters storage in the current period, and all dispatched deliveries $\sum_{k,i} \delta_{k,i,n,t}$ reduce depot inventory. This representation retains linearity and is computationally tractable, while capturing the primary effect of perishability on stored quantities. The deterioration factor reduces the quantity of finished-goods inventory that remains available in subsequent periods. Consequently, inventory losses may require additional production and raw-material procurement to satisfy future demand, thereby influencing the overall procurement, production, and distribution decisions of the supply chain.

(C6) An initial condition $I_{n,0} = 0$ is imposed, meaning that no finished-goods inventory is available at the beginning of the planning horizon.

Constraint (C7) ensures that deliveries cannot exceed the physically available inventory after deterioration and production. This constraint prevents unrealistic solutions in which demand is satisfied without sufficient stock.

Cold-Storage constraints

$$\sum_n I_{n,t} \leq Cap^{stor} \quad \forall t \in T \quad (C8)$$

(C8) The cold-storage capacity constraint limits the total finished-goods inventory that can be stored at the depot in each planning period. The parameter Cap^{stor} represents the maximum storage capacity of the cold-storage facility, measured in equivalent product units. Only finished-goods inventory $I_{n,t}$ is subject to this constraint, while raw-material inventory $MatInv_{r,t}$ is stored separately at the production facility and is therefore excluded from the cold-storage capacity limitation. By aggregating inventory across all product types, the model enforces a global storage limit that ensures production and inventory decisions remain feasible with respect to the available cold-storage space. This constraint prevents unrealistic accumulation of finished-goods and maintains consistency between production planning and storage availability.

Distributionally-robust demand satisfaction (marginal DRO)

$$\begin{aligned} \sum_{k \in K} \delta_{k,i,n,t} & \quad \forall i \in I, n \in N, \quad (C9) \\ & \quad t \in T \\ & \quad \varepsilon \in (0,1) \\ & \geq (\mu_{i,n,t} + \sqrt{\frac{1 - \varepsilon_{DRO}}{\varepsilon_{DRO}}} \sigma_{i,n,t}) \sum_{j \in V} \sum_{k \in K} X_{j,i,k,t} \end{aligned}$$

(C9) enforces demand satisfaction under distributional uncertainty using a marginal DRO approach. Retailer demand for each product and period is characterized by an empirical mean $\mu_{i,n,t}$ and standard deviation $\sigma_{i,n,t}$. The required delivered quantity equals the mean demand

augmented by a robustness margin $\sqrt{\frac{1 - \varepsilon_{DRO}}{\varepsilon_{DRO}}} \sigma_{i,n,t}$, where ε represents the risk tolerance parameter. This formulation provides a conservative demand requirement based on the first two moments of demand (mean and standard deviation) and offers distributionally robust protection against demand uncertainty controlled by the risk parameter ε_{DRO} . Unlike the base model of Hashemi-Amiri et al. (2023), where uncertainty is incorporated through vehicle-capacity constraints, the proposed formulation applies DRO directly to demand satisfaction. As a result, demand uncertainty influences procurement, production, inventory, and distribution decisions throughout the cold-storage supply chain. Importantly, the constraint is conditional on retailer visitation. The right-hand side is multiplied by the sum of routing decision variables $\sum_{j,k} X_{j,i,k,t}$, ensuring that robust demand satisfaction is enforced only in periods when retailer i is served. This avoids imposing demand fulfillment in periods without delivery and maintains consistency between routing and inventory decisions.

In contrast to the base model proposed by (Hashemi-Amiri et al., 2023), which assumes time-homogeneous demand uncertainty, the present study adopts a day-dependent demand modeling approach. This extension is motivated by the availability of historical daily demand data and by the presence of systematic temporal demand variations observed in the real case study.

Specifically, the proposed formulation allows demand moments to vary across periods by introducing period-specific empirical means and standard deviations. This enables the model to explicitly capture predictable day-of-week demand patterns while applying DRO to hedge against residual uncertainty within each period.

Another important extension to the base paper model by (Hashemi-Amiri et al., 2023) is, where uncertainty enters the model indirectly through a distributionally robust vehicle-capacity constraint due to the absence of cold-storage and the assumption of immediate production-to-vehicle loading, the extended model incorporates cold-storage buffering and therefore addresses demand uncertainty directly through the demand satisfaction process. By applying DRO directly to demand satisfaction rather than to vehicle load, the revised formulation improves robustness against demand uncertainty while maintaining tractability and better reflecting the temporal decoupling between production, storage, and distribution present in real-world operations. Because this DRO reformulation is scalar and linear, it preserves the mixed-integer linear structure of the model and avoids the conic reformulations associated with the robust vehicle-capacity constraints in the base formulation.

Routing & Assignment Constraints

$$\sum_{k \in K} \sum_{j \in V} X_{j,i,k,t} = 1 \quad \forall i \in I, t \in T \quad (C10)$$

(C10) Each retailer i must be visited exactly once in every planning period. The constraint ensures complete service coverage while preventing multiple visits by different vehicles within the same period. This classical VRP constraint enforces visit coverage and avoids multiple partial visits to the same customer within a period in our problem formulation. It couples routing

decisions across vehicles and ensures that the delivery quantity variables correspond to a single servicing event per retailer per period.

$$\sum_{j \in V} X_{0,j,k,t} = V_{k,t}, \quad \forall k \in K, t \in T \quad (C11)$$

$$\sum_{i \in V} X_{i,0,k,t} = V_{k,t}$$

(C11) These constraints couple the binary activation variable $V_{k,t}$ with the vehicle's routing arcs out of and into the depot. If vehicle k is used ($V_{k,t} = 1$) it must depart the depot on exactly one outgoing arc and return on exactly one incoming arc; if not used ($V_{k,t} = 0$), it cannot depart or return. This removes degenerate routes and simplifies counting fixed vehicle costs in the objective.

Vehicle Capacity

$$\sum_{i \in I} \sum_{n \in N} w_n \delta_{k,i,n,t} \leq C_k V_{k,t} \quad \forall k \in K, t \in T \quad (C12)$$

$$\delta_{k,i,n,t} \leq U_{i,n,t}^\delta V_{k,t} \quad \forall i \in I, n \in N, k \in K, t \in T \quad (C13)$$

(C12) limits the total weight of products delivered by vehicle k in period t to its capacity C_k , conditional on vehicle activation. The binary variable $V_{k,t}$ ensures that no delivery can be assigned to a vehicle unless it is deployed in the corresponding period. If $V_{k,t} = 0$, the constraint forces all associated delivery quantities to zero; if $V_{k,t} = 1$, the total transported load must not exceed the vehicle's capacity. This formulation tightly integrates vehicle usage decisions with capacity feasibility.

(C13) ensures that deliveries can only occur if vehicle k is activated in period t . When $V_{k,t} = 0$, all associated delivery quantities are forced to zero. The upper bound $U_{i,n,t}^\delta$ is chosen consistently with the distributionally robust demand requirement, preventing overly loose relaxations.

Linking Routing and Delivered Quantities

$$\delta_{k,i,n,t} \leq U_{i,n,t}^\delta \sum_{j \in V} X_{j,i,k,t} \quad \forall i \in I, n \in N, k \in K, t \in T \quad (C14)$$

(C14) links routing decisions to delivered quantities. A vehicle can deliver product n to retailer i in period t only if it physically visits that retailer, as indicated by the existence of an incoming routing arc associated with vehicle k . When retailer i is not visited by vehicle k , the routing term $\sum_{j \in V} X_{j,i,k,t}$ equals zero, forcing $\delta_{k,i,n,t} = 0$.

When vehicle k does visit retailer i , the upper bound on the delivered quantity is relaxed to $U_{i,n,t}^\delta$, which is chosen to coincide with the distributionally robust demand level defined in

constraint (C9). This modeling choice ensures consistency between routing decisions, delivery quantities, and the distributionally robust demand satisfaction requirement, while providing a tight, data-driven bound that avoids unnecessary relaxation of the mixed-integer formulation.

Route Continuity

$$\sum_{j \in V} X_{i,j,k,t} = \sum_{j \in V} X_{j,i,k,t} \quad \forall i \in V, k \in K, t \in T \quad (C15)$$

(C15) enforces flow conservation for each vehicle in each period. For every node, the number of outgoing arcs equals the number of incoming arcs, ensuring continuous routes without fragmentation.

Together with depot departure and return constraints, this guarantees valid vehicle tours.

Self-loop Constraint

$$X_{i,i,k,t} = 0 \quad \forall i \in V, k \in K, t \in T \quad (C16)$$

(C16) eliminates self-loops by forbidding arcs of the form (i, i) . This prevents degenerate routing patterns where a retailer appears to be served without a vehicle traveling from the depot to that retailer. Combined with the depot departure/return constraints (C11), flow conservation constraints (C15), and MTZ subtour-elimination constraints, this ensures that all routes form valid depot-connected vehicle tours without isolated cycles.

Time-Window Constraints

$$\begin{aligned} ArT_{j,t} &\geq Start_{i,t} + s_i + Tr_{i,j} \\ &\quad - M_{i,j,t} (1 - X_{i,j,k,t}) \quad \forall i, j \in I, k \in K, t \in T \quad (C17) \\ M_{i,j,t} &= T^{max} \end{aligned}$$

(C17) This conditional time-propagation constraint links service-start times and travel times to compute arrival times at successor nodes. If arc (i, j) is traversed by vehicle k , the arrival at j must be at least the service-start time at i plus service duration s_i and travel time $Tr_{i,j}$. The Big-M term $M_{i,j,t}$ deactivates the inequality when the arc is not traversed.

In the original model of (Hashemi-Amiri et al., 2023), Big-M coefficients are introduced primarily within the routing time-propagation constraints to impose conditional feasibility: travel-time and service-start relations are enforced only when a vehicle traverses a given arc. When an arc is inactive, the associated constraint is relaxed through a sufficiently large Big-M value, thereby preventing unintended restrictions on arrival or departure times. This limited use of Big-M reflects the structure of the base model, in which products flow directly from production to outbound vehicles and delivery quantities are implicitly tied to the routing plan, eliminating the possibility of allocating deliveries to non-visited customers. In contrast, the extended Model incorporates cold-storage buffering, explicit delivery-quantity decisions, and early-arrival waiting behaviour, all of which generate additional conditional relationships between routing, service timing, and product flow. As a result, Big-M plays a

broader role: beyond its classical function in the time-propagation constraint, it is also employed to guarantee routing-delivery consistency by ensuring that positive delivery quantities may be assigned to a vehicle only if that vehicle physically visits the corresponding retailer. This additional conditional structure is necessary because delivery quantities are decision variables in the extended model, whereas they are implicitly determined by production sequencing in the base formulation. Consequently, Big-M in Extended Model safeguards logical feasibility across multiple layers of the supply chain, procurement, storage, routing, and delivery, while preserving the linearity and tractability of the mixed-integer optimization model.

$$Start_{i,t} = \max\{ArT_{i,t}, ER_i\} \quad \forall i \in I, t \in T \quad (\text{C18-Conceptual})$$

$$\begin{aligned} Start_{i,t} &\geq ArT_{i,t}, \\ Start_{i,t} &\geq ER_i \end{aligned} \quad \forall i \in I, t \in T \quad (\text{C18})$$

$$Start_{0,t} = 0 \quad \forall t \in T \quad (\text{C19})$$

(C18) enforces that the service start time at customer i cannot be earlier than the vehicle arrival time nor earlier than the retailer's earliest allowed service time ER_i . Together with definitions of waiting and arrival, these inequalities realize the max operator in linear form. At optimality, the service-start time equals the maximum of the arrival time and the retailer's earliest allowable service time, thereby reproducing the conceptual max operator in linear form.

(C19) Constraint is included for conceptual completeness and defines the depot as the temporal reference point of the routing schedule. Since no service or waiting activities occur at the depot, the implementation does not introduce an explicit depot start-time variable. Omitting this variable does not affect feasibility or optimality and slightly reduces model size.

$$Wait_{i,t} = Start_{i,t} - ArT_{i,t} \quad \forall i \in I, t \in T \quad (\text{C20})$$

(C20) Waiting time captures the nonnegative difference between the service start time and the vehicle's arrival time at retailer i and waiting occurs only when a vehicle arrives before the earliest feasible service time. In the baseline formulation, waiting is not penalized in the objective function, reflecting the assumption that refrigerated vehicles can safely hold products without incurring significant freshness loss. Nevertheless, retaining the $Wait_{i,t}$ variable is operationally important: it allows the model to represent early arrivals explicitly, separate waiting effects from inventory or freshness dynamics, and enables future extensions, such as incorporating driver time costs or conducting sensitivity analysis on waiting penalties, without altering the structural formulation.

$$L_{i,t} \geq Start_{i,t} - LT_i, \quad \forall i \in I, t \in T \quad (\text{C21})$$

(C21) models service lateness as the nonnegative deviation of the service start time beyond the latest allowable service time LT_i . If service begins no later than LT_i , the right-hand side becomes nonpositive and the nonnegative lateness variable takes value zero at optimality;

otherwise, $L_{i,t}$ captures the magnitude of tardiness. Nonnegativity of $L_{i,t}$ is enforced through variable bounds. The resulting lateness is penalized in the objective function via the goodwill-loss term, allowing controlled violations of time windows when necessary.

Subtour Elimination Constraints (MTZ)

$$\begin{aligned}
 u_{i,k,t} - u_{j,k,t} + U_{\max} X_{i,j,k,t} &\leq U_{\max} - 1 & \forall i \in V \setminus \{0\}, \forall \epsilon \in \{0\}, & \quad (C22) \\
 & & i \neq j, & \\
 & & k \in K, \quad t \in T & \\
 1 \leq u_{i,k,t} &\leq U_{\max} & & \\
 U_{\max} = |V| - 1 & & \forall i \in V \setminus \{0\}, & \\
 & & k \in K, \quad t \in T &
 \end{aligned}$$

(C22) The MTZ inequalities eliminate subtours by imposing a consistent ordering $u_{i,k,t}$ of visited customers within each vehicle route. When arc (i, j) is selected, the inequality forces the order numbers to reflect a forward progression; if the arc is not used the inequality is relaxed by the $U_{\max}$ multiplier. Since the ordering variables are defined only for retailer nodes, no explicit depot-order variable is required. The MTZ formulation is applied over the retailer set I , with bounds $1 \leq u_{i,k,t} \leq U_{\max}$. The MTZ upper bound is set to $U_{\max} = |V| - 1$, corresponding to the maximum number of customer visits a vehicle can make in any period. This ensures that the order variables $u_{i,k,t}$ can represent a valid topological ordering of visited nodes while preventing subtours. The choice $U_{\max} = |V| - 1$ is standard in MTZ formulations and provides a tight and numerically stable bound.

Unlike (Hashemi-Amiri et al., 2023), the extended model developed in this thesis incorporates cold-storage, early arrivals with waiting, and multi-period VRPTW routing, which decouples production from vehicle departures and substantially increases routing flexibility. Consequently, the simple subtour-preventing structure of the original model is no longer sufficient. To ensure route feasibility in the generalized VRPTW setting, MTZ ordering constraints are introduced. MTZ is a widely adopted polynomial-size subtour-elimination method that guarantees topological consistency of each vehicle route while maintaining linearity and computational tractability for the problem sizes considered in this study.

3.3.3 Multi-objectives solution approach

To address the conflicting objectives of minimizing total supply chain cost and minimizing CO₂ emissions, a multi-objective optimization approach is required. Initially, this study implemented a **Weighted Goal Programming (WGP)** formulation, following the methodology adopted in the base study of (Hashemi-Amiri et al., 2023). In this formulation, each objective is associated with a target value obtained from solving the corresponding single-objective optimization problem.

The ideal objective values G_1^* and G_2^* represent the minimum achievable total cost and minimum achievable emissions, respectively. These values are obtained by optimizing each objective independently over the same feasible region as the integrated model. The WGP

formulation then introduces deviation variables to measure the extent to which the solution deviates from these targets.

The goal constraints can be expressed as:

$$\begin{aligned} Z_{cost} - D_1^+ + D_1^- &= G_1^* \\ Z_{CO_2} - D_2^+ + D_2^- &= G_2^* \end{aligned}$$

where D_i^+ and D_i^- denote the positive and negative deviations from the corresponding goal. Since both objectives are formulated as minimization problems, only the positive deviations D_i^+ , representing underachievement relative to the ideal targets, are penalized in the WGP objective function.

The WGP objective function is defined as:

$$\min \psi = W_1 \frac{D_1^+}{G_1^*} + W_2 \frac{D_2^+}{G_2^*}$$

subject to:

$$W_1 + W_2 = 1, W_1, W_2 > 0$$

The normalization by the ideal objective values ensures that deviations from the two objectives are expressed on a comparable scale.

However, after extending the model to incorporate raw material inventory decisions, the WGP formulation exhibited significant computational difficulties. In particular, the solver was unable to reduce the optimality gap within the imposed time limit, indicating numerical instability and increased model complexity. This issue is partly attributable to the large difference in magnitude between the cost and emission objectives, as well as the additional variables introduced by the deviation-based formulation.

To overcome these limitations, the ε -constraint method was adopted as the primary multi-objective solution approach. In this method, one objective is optimized while the other objective is transformed into a constraint. Specifically, the model minimizes the total supply chain cost while restricting emissions within a predefined bound:

$$Z_{CO_2} \leq (1 + \varepsilon_{emmission})G_2^*$$

where G_2^* is the minimum achievable emission level and ε represents the allowable percentage relaxation from this target.

By varying the ε parameter, multiple efficient solutions can be generated, enabling a systematic exploration of the trade-off between economic cost and environmental impact. This approach provides a stable computational framework while allowing decision-makers to evaluate different policy scenarios balancing cost efficiency and emission reduction.

(Two different ε parameters are used in this study. The first ε defines the size of the ambiguity set in the DRO framework, controlling the confidence level of the uncertainty set. The second

ε is used in the ε -constraint method for multi-objective optimization, where environmental impact is bounded while minimizing economic cost).

3.4 Solution Approach

The proposed optimization model was formulated as a MILP model and implemented in Python using the Gurobi Optimizer. The model integrates procurement, production planning, inventory management, and vehicle routing decisions within a multi-period perishable food supply chain framework.

All optimization experiments were conducted using Gurobi version 12.0.3 on a computer equipped with an Apple M1 processor and 8 GB of RAM. To balance computational efficiency and solution quality, the relative optimality gap parameter (MIPGap) was set to 1%. The optimality gap represents the difference between the best feasible solution found and the best lower bound identified by the solver. Consequently, the reported solutions correspond to the best solutions obtained within a 1% tolerance of the proven optimum.

The benchmark objective values were first obtained by optimizing each objective independently. Subsequently, the ε -constraint method was used to generate Pareto-efficient solutions under different emission limits. The computational performance of each scenario, including runtime and optimality gap, is reported in Chapter 4.

3.5 Case Study Description

3.5.1 Background and Industrial Context

This study is based on a real-world case from a **mid-sized convenient meal manufacturer operating in Mongolia**. The company collaborates with multiple suppliers, produces several types of ready-to-eat meals, and distributes them to a network of urban retailers within Ulaanbaatar, the capital city of Mongolia, over a finite planning horizon. The production facility operates under limited capacity, while the central cold-storage is subject to space constraints. The products are perishable and exhibit quality deterioration during storage and distribution. Customer demand varies across retailers and planning periods, creating uncertainty in procurement, production, and distribution decisions. The company operates a homogeneous fleet of vehicles with fixed capacity, and deliveries must be completed within limited time frames to preserve product quality and it produces six categories of perishable ready-to-eat food products and collaborates with a network of 29 suppliers and 43 retail customers within Ulaanbaatar. Distribution activities are performed using a fleet of seven delivery vehicles. The resulting supply chain structure reflects the operational complexity faced by many medium-sized food manufacturers, where procurement, production, storage, and distribution decisions must be coordinated under perishability and demand uncertainty. Due to computational considerations, a reduced instance was constructed for numerical experimentation while preserving the key structural characteristics of the original supply chain.

The company sources multiple raw materials from a set of suppliers, all located within Ulaanbaatar. Although suppliers are geographically concentrated, they differ in terms of capacity, procurement cost, and material availability, creating trade-offs in supplier allocation and sourcing decisions. The raw materials are combined through multi-ingredient production processes to produce finished meals, which are temporarily stored in a central cold-storage facility before being distributed to a network of urban retailers. Due to the perishable nature of

the products, inventory deterioration occurs continuously during storage, and delivery delays may result in quality loss, waste, or customer dissatisfaction.

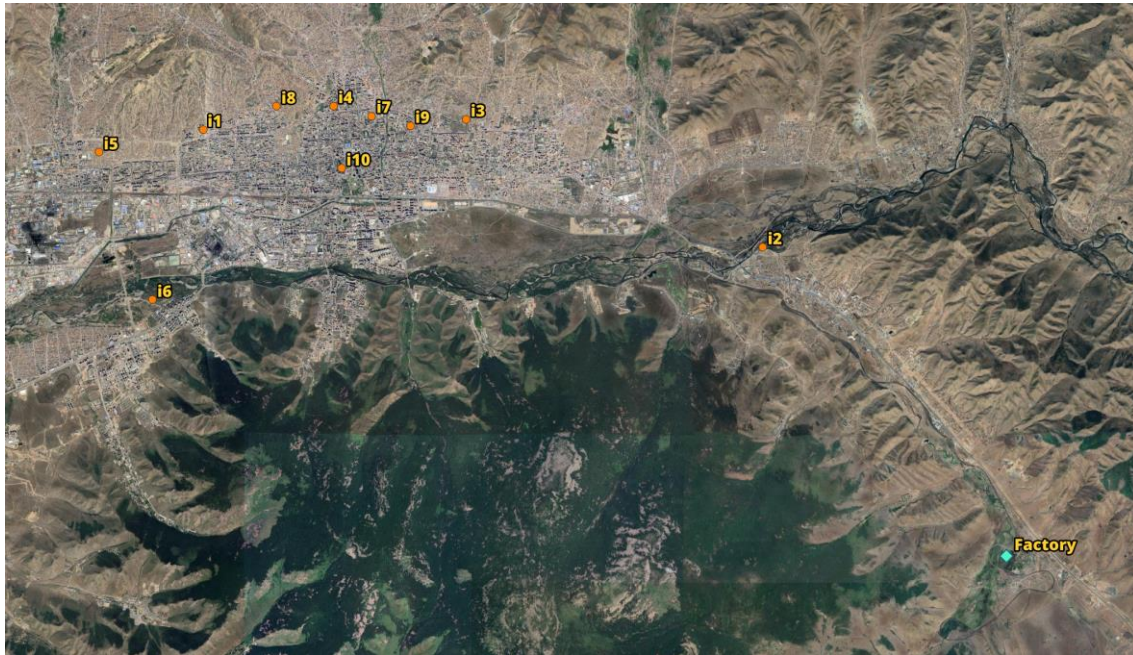


Figure 3.1 The geographical locations of the retailers and the factory
Source: Case study data

Operational planning at the company is challenging because procurement, production, inventory management, and distribution decisions are strongly interdependent. Supplier deliveries determine the availability of raw materials for production, production schedules influence inventory levels and product freshness, and routing decisions affect both service performance and transportation-related emissions. Consequently, decisions taken at one stage of the supply chain propagate throughout the entire planning system, making isolated optimization approaches difficult to justify in practice. Traditionally, these decisions are handled sequentially, which often leads to infeasible or suboptimal outcomes in practice. This case study therefore provides an appropriate real-world context for evaluating an integrated optimization approach for perishable food supply chain management.

The data used in this case study are derived from the internal operational records of the case company. To preserve confidentiality, all company-identifying information has been removed, and product, supplier, and retailer names have been anonymized. Cost and demand parameters are presented using a consistent scaling approach that preserves realistic operational magnitudes while maintaining the relative relationships observed in the original dataset.

3.5.2 Supply Chain Structure and Planning Horizon

The supply chain considered in this case study consists of four main echelons: suppliers, a production facility with central cold-storage, a vehicle fleet, and retailers. Raw materials are procured from a fixed set of suppliers and delivered to the production facility with a deterministic lead time of one planning period. Upon arrival, raw materials are stored at the production site and are subject to inventory balance constraints over the planning horizon. The inventory level in each period is determined by the previous inventory, incoming deliveries, and material consumption driven by production decisions. Holding costs are incurred for stored

raw materials, thereby capturing the financial impact of capital binding and storage requirements. This ensures that procurement decisions are coordinated with production planning and discourages excessive inventory accumulation.

Production is carried out in batches and is constrained by an aggregated production capacity, reflecting the operational reality of the firm. This modeling choice is typical for small and medium-sized manufacturing companies in Mongolia, where total production throughput rather than detailed machine-level scheduling represents the primary operational bottleneck.

Finished products are stored in a central cold-storage facility prior to distribution. Inventory is subject to capacity limitations and continuous deterioration, meaning that a fixed fraction of stored products is lost in each period due to spoilage. This modeling approach captures the dominant effect of perishability while remaining computationally tractable.

Distribution is performed from the central depot to a set of retailers using a homogeneous fleet of refrigerated vehicles. Each retailer must be served exactly once per period by a single vehicle, and deliveries must respect vehicle capacity limits and retailer-specific time windows. Routing decisions, delivery quantities, and vehicle usage are jointly determined within the optimization model to ensure operational consistency.

3.5.3 Demand Characteristics and Uncertainty

Retailer demand for finished products is inherently uncertain and varies across both products and locations. Demand in the case company also exhibits clear temporal patterns. Many retail outlets are located near schools and universities, resulting in consistently higher demand during weekdays and lower demand during weekends. Such fluctuations reflect the daily consumption habits of customers and create recurring variations in replenishment requirements throughout the planning horizon.

For the purposes of this study, eight weeks of historical daily demand data were obtained for each retailer-product combination. These observations provide valuable information regarding recent demand patterns and variability while also revealing pronounced day-of-week effects. Given the limited sample size and the presence of systematic temporal demand fluctuations, specifying a precise probability distribution for future demand would be difficult and potentially unreliable.

To address this uncertainty, the study adopts a DRO framework. Historical observations are used to estimate day-specific demand characteristics, including the empirical mean and variability of demand for each retailer-product pair. Based on these estimates, separate ambiguity sets are constructed for each day of the planning horizon, allowing demand uncertainty to vary across periods. The resulting model seeks solutions that remain feasible under the worst-case distribution within each ambiguity set, thereby accounting for both recurring weekday-weekend demand patterns and residual uncertainty in future demand realizations.

From an operational perspective, demand is treated as a service requirement rather than a fixed deterministic target. Consequently, procurement, production, inventory, and routing decisions are determined in a coordinated manner while ensuring that minimum service levels are maintained. This reflects the practical reality faced by managers, who must commit resources before actual demand becomes known.

Overall, the adopted demand representation balances realism and tractability by combining observed demand patterns with robustness against uncertain future demand realizations. This enables the integrated planning model to generate solutions that remain feasible across a range of plausible operating conditions.

3.5.4 Key Operational Constraints

Several practical constraints shape the planning problem in this case study. Supplier capacities limit the amount of raw materials that can be procured in each period, while production capacity restricts the total output of finished products. Cold-storage capacity and inventory deterioration constrain how much inventory can be carried forward between periods. On the distribution side, vehicle availability, vehicle capacity, travel distances, and retailer time windows restrict feasible routing and delivery plans.

In addition to economic considerations, transportation-related CO₂ emissions are explicitly accounted for, reflecting the environmental impact of refrigerated distribution. Emissions are modeled as a function of travel distances and vehicle-specific emission factors, which allows the analysis to evaluate trade-offs between economic performance and environmental sustainability.

3.5.5 Purpose of the Case Study

The purpose of this case study is to evaluate the practical applicability of the proposed EIPAPRP model under realistic operational conditions. By utilizing data derived from an actual food manufacturing company, the study examines how procurement, production, inventory, and distribution decisions can be coordinated within a unified optimization framework while accounting for perishability, demand uncertainty, and sustainability considerations.

The analysis focuses on short-term operational and tactical planning decisions over a one-week planning horizon. The model simultaneously determines raw-material procurement quantities, production quantities, inventory levels for both raw materials and finished products, and vehicle routing plans for retailer deliveries. These decisions reflect the core planning activities performed by the company on a regular basis and are therefore well suited for evaluating the practical relevance of the proposed framework.

To balance model realism and computational tractability, the optimization experiments are conducted on a reduced but representative version of the original supply chain. While the company produces six categories of perishable food products, collaborates with 29 suppliers, serves 43 retail customers, and operates a fleet of seven vehicles, the computational instance uses a representative subset of products, suppliers, raw materials, and retailers. This reduction preserves the structural characteristics and operational relationships observed in the real system while maintaining manageable solution times for the integrated optimization model.

The resulting case study provides a realistic yet computationally tractable environment for assessing the effectiveness of integrated planning in perishable food supply chains. At the same time, it enables the evaluation of how the proposed model addresses key operational challenges associated with procurement coordination, inventory deterioration, cold-storage management, and distribution planning under uncertainty.

3.5.6 Case Study Parameters

This section presents the numerical parameters used in the case study.

The parameters are organized according to the main decision layers of the integrated model: demand, procurement, production, inventory, and distribution.

3.5.7 Sets and Indices

Table 3.4 Case study Sets

<i>Set</i>	<i>Description</i>	<i>Cardinality</i>
Q	Suppliers	5
R	Raw materials	10
N	Finished products	3
I	Retailers	10
K	Vehicles	4
T	Time periods (days)	7

Based on the operational data provided by the case company, the PFSC network under study consists of five supplier centers, ten types of raw materials, three finished products, four homogeneous refrigerated vehicles, and ten retailers that must be served over a one-week planning horizon. The planning horizon is divided into seven daily periods, with an additional initial period dedicated exclusively to raw material procurement to account for procurement lead time.

Table 3.5 Day - Dependent Mean and Standard Deviation of the probabilistic demands

Product	t1 ($\mu \pm \sigma$)	t2 ($\mu \pm \sigma$)	t3 ($\mu \pm \sigma$)	t4 ($\mu \pm \sigma$)	t5 ($\mu \pm \sigma$)	t6 ($\mu \pm \sigma$)	t7 ($\mu \pm \sigma$)
Retailer 1							
n1	58.13 $\pm$ 11.14	56.75 $\pm$ 7.65	56.63 $\pm$ 8.16	57.00 $\pm$ 8.33	49.25 $\pm$ 8.83	39.75 $\pm$ 6.56	36.63 $\pm$ 4.53
n2	47.25 $\pm$ 9.98	53.88 $\pm$ 9.09	49.88 $\pm$ 9.43	49.00 $\pm$ 9.10	45.88 $\pm$ 6.90	39.38 $\pm$ 8.25	37.50 $\pm$ 7.96
n3	44.00 $\pm$ 5.78	46.38 $\pm$ 6.44	47.25 $\pm$ 6.25	42.63 $\pm$ 7.41	40.38 $\pm$ 6.68	33.63 $\pm$ 3.70	30.38 $\pm$ 1.06
Retailer 2							
n1	52.13 $\pm$ 6.58	60.88 $\pm$ 9.42	58.50 $\pm$ 9.27	53.50 $\pm$ 6.99	49.38 $\pm$ 4.41	42.75 $\pm$ 5.18	36.63 $\pm$ 4.63
n2	44.75 $\pm$ 5.45	49.88 $\pm$ 6.06	46.00 $\pm$ 3.30	48.88 $\pm$ 3.56	44.00 $\pm$ 4.96	34.75 $\pm$ 3.41	31.88 $\pm$ 2.42
n3	43.50 $\pm$ 4.54	46.25 $\pm$ 6.30	43.00 $\pm$ 7.48	42.13 $\pm$ 7.04	41.75 $\pm$ 5.68	33.63 $\pm$ 4.21	31.38 $\pm$ 1.69
Retailer 3							
n1	57.13 $\pm$ 9.95	60.50 $\pm$ 10.92	62.88 $\pm$ 12.08	55.63 $\pm$ 5.04	53.00 $\pm$ 6.12	41.75 $\pm$ 6.88	39.13 $\pm$ 5.14
n2	52.88 $\pm$ 8.06	52.25 $\pm$ 7.52	55.88 $\pm$ 8.64	50.88 $\pm$ 3.80	48.13 $\pm$ 4.19	39.13 $\pm$ 6.01	36.13 $\pm$ 7.18
n3	43.75 $\pm$ 6.65	45.25 $\pm$ 7.09	44.88 $\pm$ 7.75	43.50 $\pm$ 5.32	40.25 $\pm$ 5.63	32.13 $\pm$ 2.53	31.75 $\pm$ 2.55
Retailer 4							
n1	53.63 $\pm$ 4.21	56.25 $\pm$ 4.65	55.88 $\pm$ 5.67	56.00 $\pm$ 9.41	47.38 $\pm$ 6.21	41.00 $\pm$ 8.37	38.13 $\pm$ 5.57
n2	53.00 $\pm$ 5.95	52.63 $\pm$ 7.62	54.50 $\pm$ 10.61	53.50 $\pm$ 7.52	46.50 $\pm$ 5.90	38.25 $\pm$ 5.09	36.75 $\pm$ 5.20
n3	46.50 $\pm$ 5.16	49.00 $\pm$ 12.39	46.50 $\pm$ 6.93	46.00 $\pm$ 5.56	40.50 $\pm$ 4.31	32.13 $\pm$ 2.42	31.50 $\pm$ 2.51

Table 3.5 (Continued)

Product	t1 ($\mu \pm \sigma$)	t2 ($\mu \pm \sigma$)	t3 ($\mu \pm \sigma$)	t4 ($\mu \pm \sigma$)	t5 ($\mu \pm \sigma$)	t6 ($\mu \pm \sigma$)	t7 ($\mu \pm \sigma$)
Retailer 5							
n1	57.63 $\pm$	59.38 $\pm$	62.38 $\pm$	58.25 $\pm$	53.13 $\pm$	41.13 $\pm$	38.25 $\pm$
	5.07	5.55	7.29	7.44	6.29	5.82	3.37
n2	50.75 $\pm$	51.75 $\pm$	53.13 $\pm$	49.13 $\pm$	46.00 $\pm$	38.38 $\pm$	37.13 $\pm$
	7.03	7.57	7.16	6.71	5.53	3.54	4.55
n3	45.50 $\pm$	46.50 $\pm$	49.25 $\pm$	44.50 $\pm$	39.25 $\pm$	34.50 $\pm$	31.88 $\pm$
	4.07	3.96	6.74	4.60	5.68	3.34	2.95
Retailer 6							
n1	57.88 $\pm$	59.75 $\pm$	58.75 $\pm$	53.38 $\pm$	49.50 $\pm$	39.50 $\pm$	38.75 $\pm$
	6.56	9.02	7.15	8.16	5.66	5.26	4.40
n2	46.50 $\pm$	51.00 $\pm$	46.50 $\pm$	48.50 $\pm$	43.50 $\pm$	33.75 $\pm$	36.50 $\pm$
	5.90	8.91	4.50	7.75	3.12	2.96	6.28
n3	44.13 $\pm$	46.13 $\pm$	47.88 $\pm$	42.00 $\pm$	39.13 $\pm$	33.50 $\pm$	31.00 $\pm$
	6.94	5.14	9.49	7.41	5.54	3.12	1.20
Retailer 7							
n1	53.63 $\pm$	59.13 $\pm$	57.38 $\pm$	53.50 $\pm$	53.38 $\pm$	42.63 $\pm$	37.63 $\pm$
	10.38	10.19	7.86	11.54	8.35	7.37	4.93
n2	49.13 $\pm$	52.50 $\pm$	54.63 $\pm$	54.50 $\pm$	47.88 $\pm$	38.63 $\pm$	35.50 $\pm$
	9.80	9.40	10.07	8.40	7.77	4.84	5.93
n3	47.00 $\pm$	46.13 $\pm$	47.63 $\pm$	45.13 $\pm$	40.88 $\pm$	36.00 $\pm$	33.50 $\pm$
	5.16	4.73	8.00	4.19	4.16	4.54	3.07
Retailer 8							
n1	58.25 $\pm$	62.75 $\pm$	61.88 $\pm$	63.25 $\pm$	54.63 $\pm$	42.25 $\pm$	40.38 $\pm$
	7.27	7.25	9.76	5.85	9.72	8.05	4.00
n2	48.00 $\pm$	56.63 $\pm$	52.38 $\pm$	54.63 $\pm$	47.00 $\pm$	37.63 $\pm$	35.63 $\pm$
	4.99	6.82	6.48	6.30	5.56	3.78	4.78
n3	46.00 $\pm$	48.00 $\pm$	48.88 $\pm$	46.50 $\pm$	43.75 $\pm$	33.13 $\pm$	32.13 $\pm$
	5.56	4.66	6.22	7.58	4.43	2.80	2.64
Retailer 9							
n1	59.75 $\pm$	62.75 $\pm$	57.63 $\pm$	56.88 $\pm$	51.38 $\pm$	42.38 $\pm$	41.63 $\pm$
	10.59	8.78	7.60	7.86	8.88	7.21	3.34
n2	49.75 $\pm$	51.63 $\pm$	52.50 $\pm$	50.88 $\pm$	43.88 $\pm$	34.50 $\pm$	33.75 $\pm$
	9.54	7.15	8.42	5.77	8.20	4.31	4.40
n3	43.13 $\pm$	49.00 $\pm$	47.25 $\pm$	42.13 $\pm$	42.25 $\pm$	32.50 $\pm$	31.38 $\pm$
	8.22	8.19	7.67	4.61	7.19	4.00	1.92
Retailer 10							
n1	57.63 $\pm$	62.38 $\pm$	63.00 $\pm$	60.13 $\pm$	53.63 $\pm$	42.00 $\pm$	39.88 $\pm$
	6.68	6.07	4.63	5.28	5.40	4.31	4.85
n2	53.88 $\pm$	53.38 $\pm$	50.75 $\pm$	45.63 $\pm$	48.63 $\pm$	36.25 $\pm$	35.75 $\pm$
	8.25	6.21	6.16	4.66	5.53	3.92	2.61
n3	44.38 $\pm$	49.00 $\pm$	47.25 $\pm$	45.63 $\pm$	40.88 $\pm$	34.50 $\pm$	32.38 $\pm$
	8.55	10.28	8.89	5.66	4.70	5.13	3.42

Table 3.5 reports the empirical mean (μ) and standard deviation (σ) of daily demand for each retailer-product pair, estimated separately for each day of the planning horizon using eight weeks of historical data.

Table 3.6 The set of predefined time windows for serving customers

Parameter		ER_i	LT_i
Retailer 1	i1	420	600
Retailer 2	i2	360	600
Retailer 3	i3	420	660
Retailer 4	i4	420	660
Retailer 5	i5	540	780
Retailer 6	i6	300	540
Retailer 7	i7	540	780
Retailer 8	i8	480	660
Retailer 9	i9	420	660
Retailer 10	i10	360	600

Table 3.6 shows the set time windows for each retailer. The ER_i marks the earliest time when service can start, and the LT_i marks the latest time allowed. Deliveries must occur within these time windows to ensure service is on time and customers are satisfied. The time windows are different for each retailer because their operations and demand are not the same. These time windows are added to the model as constraints to help with routing and scheduling.

Table 3.7 Summary of Supplier Parameters

Raw material	No. of suppliers	Capacity range (units)	Price range (per unit)
Rice	r1	2	70 - 100
Oil	r2	2	7 - 13
Spices	r3	2	10 - 14
Chicken meat	r4	2	18 - 25
Tuna	r5	2	16 - 24
Seaweed (pcs)	r6	2	700 - 1,200
Vegetable mix	r7	2	30 - 40
Soya sauce	r8	2	14 - 16
Beef tenderloin	r9	2	35 - 45
Plastic roll (pcs)	r10	2	715 - 1,250

Table 3.7 shows the main supplier parameters for each raw material in the model. Each material has two suppliers, and each supplier has a certain capacity range and unit price range. These ranges indicate that supply and cost can vary, allowing the model to choose different sourcing options. The differences between materials, especially in capacity and price, are important for procurement decisions in the optimization model.

Table 3.8 The production cost and time of final products

Parameter		n1	n2	n3
Production cost	c_n^{prod}	300	250	250
Inventory cost	h_n	20	15	15
Storage Deterioration Beta	β_n	0.035	0.025	0.025

Table 3.8 presents the key production-related parameters for the final products $n1$, $n2$, and $n3$. It includes the unit production cost, inventory holding cost, and deterioration rate for each product. The deterioration parameter captures product perishability during storage, while inventory costs reflect the cost of holding goods over time. These parameters are incorporated

into the model to balance production, storage, and waste, thereby influencing optimal production planning and inventory decisions.

Table 3.9 Distance matrix between cold-storage and retailers

		Cold-storage	Retailer 1	Retailer 2	Retailer 3	Retailer 4	Retailer 5	Retailer 6	Retailer 7	Retailer 8	Retailer 9	Retailer 10
		i0	i1	i2	i3	i4	i5	i6	i7	i8	i9	i10
Cold-storage	i0	0	30.25	13.11	23.25	27.92	33.38	30.53	27.56	29.17	27.02	26.52
Retailer 1	i1	30.25	0	20.41	9.23	4.45	4.18	5.88	5.44	2.33	4.91	4.73
Retailer 2	i2	13.11	20.41	0	4.73	15.06	20.52	17.67	14.69	16.31	14.16	13.65
Retailer 3	i3	23.25	9.23	4.73	0	4.95	12.44	14.89	3.87	6.34	2.95	4.43
Retailer 4	i4	27.92	4.45	15.06	4.95	0	9.46	7.71	1.4	3.84	1.37	1.69
Retailer 5	i5	33.38	4.18	20.52	12.44	9.46	0	6.85	8.93	5.02	8.39	7.2
Retailer 6	i6	30.53	5.88	17.67	14.89	7.71	6.85	0	8.19	7.21	7.65	7.19
Retailer 7	i7	27.56	5.44	14.69	3.87	1.4	8.93	8.19	0	4.18	0.71	2.13
Retailer 8	i8	29.17	2.33	16.31	6.34	3.84	5.02	7.21	4.18	0	3.36	4.67
Retailer 9	i9	27.02	4.91	14.16	2.95	1.37	8.39	7.65	0.71	3.36	0	1.48
Retailer 10	i10	26.52	4.73	13.65	4.43	1.69	7.2	7.19	2.13	4.67	1.48	0

Table 3.9 presents the distance matrix between the cold-storage facility and all retailers, as well as the distances among retailers themselves. These distances represent the transportation network used in the routing component of the model. The matrix is symmetric, indicating that travel distances between locations are identical in both directions. This information is essential for calculating transportation costs, making routing decisions, and scheduling vehicles, as it directly influences route optimization and overall distribution efficiency.

4. Computational and Sensitivity Analysis Results

4.1 Computational Results

4.1.1 Results and Discussion of the Bi-Objective Model

Table 4.1 Goal values of the bi-objective model.

Objective benchmark	Values	Unit
G_1	39,144,900.47	Tugriks (₮)
G_2	838.11	kg CO ₂

The benchmark solutions reported in Table 4.1 were obtained by solving each objective separately. The minimum economic cost achieved by the model is 39,144,900.47 ₮, whereas the minimum transportation-related CO₂ emission level is 838.11 kg CO₂. These values represent the ideal solutions for each objective considered separately and serve as benchmark points for the subsequent bi-objective analysis.

The benchmark solutions define the lower bounds of the objective space and provide the basis for generating Pareto-efficient solutions using the ε -constraint method. By comparing the benchmark values with the results obtained under different ε levels, it becomes possible to evaluate the trade-offs between economic and environmental performance within the proposed integrated PFSC framework.

4.1.2. Trade-Off Analysis of the ε -Constraint Model

Table 4.2 *Computational results of the ε -constraint model for the case study problem.*

ε (%)	Achieved Total Cost (¥)	Achieved Total Emissions (kg CO ₂)	Model Gap (%)	Runtime (sec)
0	60,586,047.53	838.11	35.85	9,315.17
2	43,183,980.67	854.15	9.83	71,446.48
5	39,158,185.67	872.03	0.78	225.54
10	39,072,304.47	890.6	0.99	0.33

Table 4.2 presents the computational results obtained using the ε -constraint method for different emission limits. The results reveal a clear trade-off between economic cost and environmental performance. As the emission constraint is gradually relaxed from $\varepsilon = 0\%$ to $\varepsilon = 10\%$, the total supply chain cost decreases from 60.59 million ¥ to 39.07 million ¥, while transportation-related CO₂ emissions increase from 838.11 kg CO₂ to 890.60 kg CO₂.

(All scenarios were solved using a relative optimality gap of 1%; therefore, the reported objective values represent the best solutions found within the specified optimality tolerance).

The largest improvement occurs when moving from the strict environmental benchmark ($\varepsilon = 0\%$) to moderate relaxation levels. Increasing ε from 0% to 2% reduces total cost by approximately 28.7%, while emissions increase by only 1.9%. This indicates that a relatively small increase in emissions can generate substantial economic benefits. Further relaxation of the emission constraint continues to reduce costs, although the magnitude of improvement becomes progressively smaller.

Computational performance also improves substantially as the emission constraint becomes less restrictive. The strictest environmental scenario ($\varepsilon = 0\%$) required more than 2.5 hours of computation and resulted in a large optimality gap. In contrast, solutions for $\varepsilon \geq 5\%$ were obtained within a few minutes or seconds while achieving gaps below 1%, demonstrating that relaxed emission bounds allow the solver to identify high-quality solutions much more efficiently.

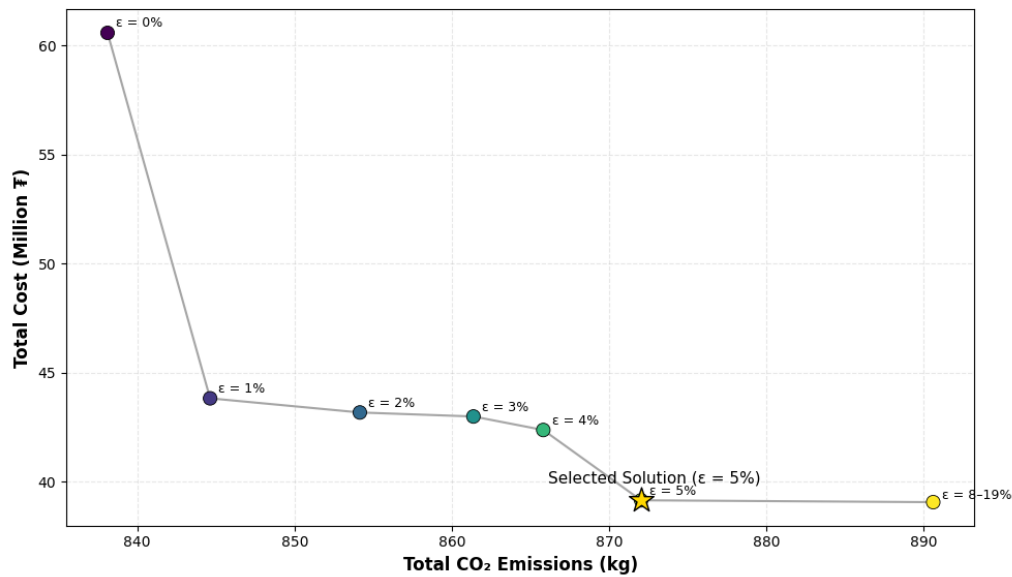


Figure 4.1 Pareto Frontier Generated by the ε -Constraint Method

Figure 4.1 illustrates the Pareto frontier generated using the ε -constraint method. The frontier confirms the existence of a non-dominated set of solutions, demonstrating the trade-off between economic cost and transportation-related CO₂ emissions. As the emission constraint is gradually relaxed, total supply chain cost decreases, while emissions increase. The shape of the frontier reveals diminishing returns from further relaxing the emission constraint. Between $\varepsilon = 5\%$ and $\varepsilon = 19\%$, only marginal or no additional cost reductions are achieved despite higher allowable emissions. This suggests that most of the attainable economic benefit is already captured at moderate relaxation levels.

The solution corresponding to $\varepsilon = 5\%$ was selected as the preferred compromise solution and is highlighted in the figure. This solution lies near the knee point of the Pareto frontier, where a substantial reduction in total cost can be achieved with only a limited increase in emissions.

Overall, the generated Pareto frontier provides decision-makers with a set of efficient alternatives and illustrates the trade-off between economic and environmental objectives within the proposed EIPAPPRP framework.

4.1.3. Procurement Allocation and Cost Distribution

Table 4.3 Total procurement by supplier

Supplier	Total Quantity Purchased	Total Procurement Cost (Tugriks (₺))
q1	1,086.89	3,982,370.56
q3	19,984.26	15,344,388.32
q4	4,806.73	4,064,912.31
q5	816.18	9,430,752.17
Total	26,694.06	32,822,423.36

Table 4.3 indicate a highly concentrated procurement structure, with substantial differences in both purchased quantities and procurement expenditures across suppliers. This pattern reflects the interaction between material requirements, supplier capacities, and procurement costs within the integrated optimization framework.

Supplier q3 accounts for the largest share of procurement activity, supplying 19,984.26 units out of a total procurement volume of 26,694.06 units. This indicates that the model relies heavily on q3 to satisfy production requirements while minimizing overall procurement costs. In contrast, suppliers q1 and q5 contribute relatively small procurement quantities and therefore play a more limited role in the optimal sourcing strategy.

The results also reveal notable differences between procurement quantities and procurement expenditures. Although supplier q5 provides only a small share of the total purchased quantity, it accounts for a substantial portion of total procurement cost. This suggests that procurement decisions are influenced not only by volume requirements but also by the material composition of finished products and the availability of specific raw materials across suppliers.

Overall, the procurement plan demonstrates how the integrated model allocates sourcing decisions across suppliers while balancing production requirements, supplier capacities, and cost considerations.

4.1.4. Procurement Distribution by Raw Material

Table 4.4 Total procurement by raw material

Raw Material	Total Quantity Purchased
r1	936.39
r2	168.94
r3	67.89
r4	177.23
r5	234.15
r6	12,803.09
r7	342.87
r8	146.47
r9	266.03
r10	9,551.00
Total	24,694.06

Table 4.4 summarizes the total procurement quantities of each raw material aggregated over the planning horizon. The results reveal a highly uneven distribution of procurement volumes across materials, indicating substantial differences in material requirements within the production system.

In particular, raw materials r6 and r10 dominate the procurement plan, with total purchased quantities of 12,803.09 and 9,551.00 units, respectively. Together, these two materials account for approximately 90% of the total procurement volume. This suggests that they represent key production inputs that are required across multiple products or in relatively large quantities within the corresponding bills of materials.

In contrast, the remaining raw materials are procured in considerably smaller quantities. Materials such as r2, r3, r4, and r8 contribute only a minor share of total procurement demand, reflecting their more limited role within the production process.

The resulting procurement structure reflects the interaction between product demand, BOM requirements, and supplier availability within the integrated planning framework.

4.1.5 Production Quantity Distribution Across Products

Table 4.5 Total production quantity

Product	Total Production Quantity	Total Production Cost (Tugriks)
n1	5,825.58	1,747,676.55
n2	5,196.32	1,298,078.80
n3	4,568.83	1,142,207.64

The results reported in Table 4.5 indicate that production is distributed across all three finished products over the planning horizon, with product n1 accounting for the largest production volume, followed by n2 and n3. Examination of the detailed production schedule presented in B. Appendix, Table B.2 reveals a gradual decline in production quantities across all products toward the end of the planning horizon. This pattern is consistent with the demand characteristics discussed in Section 3.5.3, where demand is generally higher during weekdays and lower during weekends. The model therefore adjusts production quantities over time in response to anticipated demand variations while maintaining coordination between procurement, inventory, and distribution decisions.

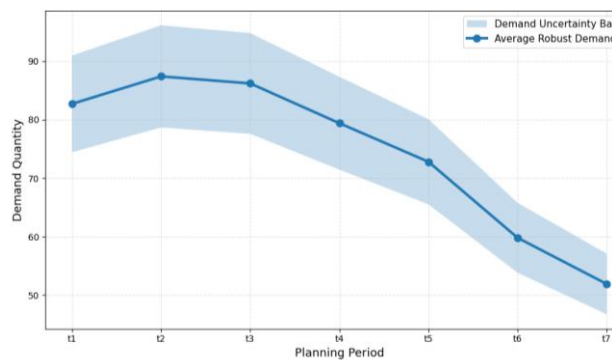


Figure 4.2 Distributionally Robust Demand Trend

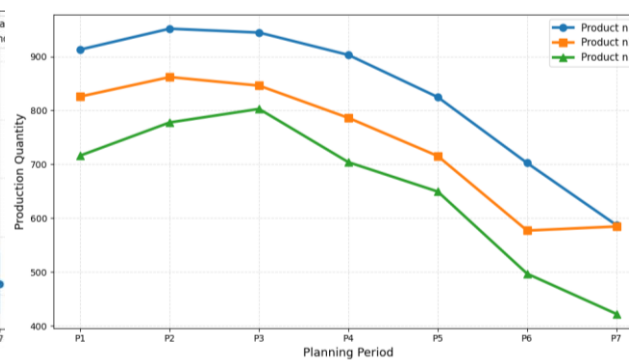


Figure 4.3 Production quantities across planning periods

The robust demand thresholds generated by the DRO framework exhibit a declining pattern after Period 3, with the highest demand occurring in Periods 2-3 and the lowest demand observed in Periods 6-7. This trend reflects the demand characteristics of the case-study network, where several retailers are located near schools and universities. As customer activity decreases toward weekends, the model anticipates lower demand levels and adjusts planning decisions accordingly. The shaded uncertainty band illustrates the range of demand realizations considered by the DRO framework, protecting demand variability while maintaining operational feasibility.

As shown in Figure 4.3, production quantities for all three products follow the same general pattern as the robust demand thresholds. Production peaks during Periods 2-3 and gradually declines toward Period 7, demonstrating the model's ability to dynamically align production decisions with anticipated demand changes. This result highlights the effectiveness of integrating demand uncertainty, production planning, and inventory management within a single optimization framework, allowing the system to avoid unnecessary production while maintaining sufficient supply throughout the planning horizon.

4.1.6 Vehicle Routing Decision

Table 4.6 Optimal routing decisions for each planning period

Period	Vehicle	Trip
t1	k1	Production Facility - 6 - 1 - 4 - 7 - Production Facility
	k2	Production Facility - 2 - 3 - Production Facility
	k3	Production Facility - 10 - 9 - 8 - 5 - Production Facility
t2	k1	Production Facility - 6 - 1 - 5 - Production Facility
	k2	Production Facility - 10 - 4 - 8 - Production Facility
	k3	Production Facility - 2 - Production Facility
	k4	Production Facility - 3 - 9 - 7 - Production Facility
t3	k1	Production Facility - 9 - 1 - 7 - Production Facility
	k3	Production Facility - 3 - 8 - 5 - Production Facility
	k4	Production Facility - 6 - 10 - 4 - 2 - Production Facility
t4	k1	Production Facility - 6 - 1 - 8 - 5 - Production Facility
	k3	Production Facility - 10 - 4 - 9 - 7 - Production Facility
	k4	Production Facility - 2 - 3 - Production Facility
t5	k1	Production Facility - 6 - 1 - 8 - 5 - Production Facility
	k3	Production Facility - 2 - 3 - Production Facility
	k4	Production Facility - 10 - 4 - 9 - 7 - Production Facility
t6	k1	Production Facility - 6 - 10 - 1 - 8 - 5 - Production Facility
	k2	Production Facility - 2 - 3 - 4 - 9 - 7 - Production Facility
t7	k1	Production Facility - 2 - 3 - 9 - 1 - 8 - 5 - Production Facility
	k4	Production Facility - 6 - 10 - 4 - 7 - Production Facility

The results reported in Table 4.6 indicate that routing decisions vary across planning periods in response to changing delivery requirements and demand levels. The number of active vehicles ranges from two to four per period, suggesting that the model dynamically adjusts fleet utilization according to the volume and the geographical distribution of customer demand. During the earlier periods (t1-t5), three or four vehicles are deployed to satisfy higher delivery requirements. In contrast, only two vehicles are required in periods t6 and t7, reflecting the reduction in production and distribution volumes observed toward the end of the planning horizon. This pattern is consistent with the temporal demand characteristics discussed in Section 3.5.3 and the declining production quantities reported in Appendix Table B.2.

The routing plans also demonstrate the model's ability to consolidate deliveries efficiently. Several routes combine geographically proximate retailers within a single tour, while maintaining feasible vehicle capacities and service schedules. By coordinating routing decisions with procurement, production, and inventory planning, the integrated framework generates delivery schedules that satisfy customer demand while limiting unnecessary transportation activity.

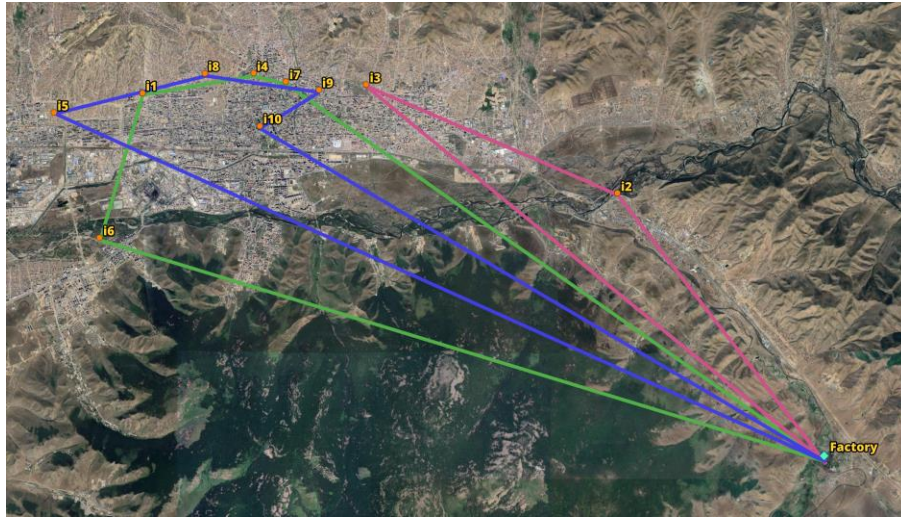


Figure 4.4 Period 1 (Medium Demand): 3 vehicles utilized

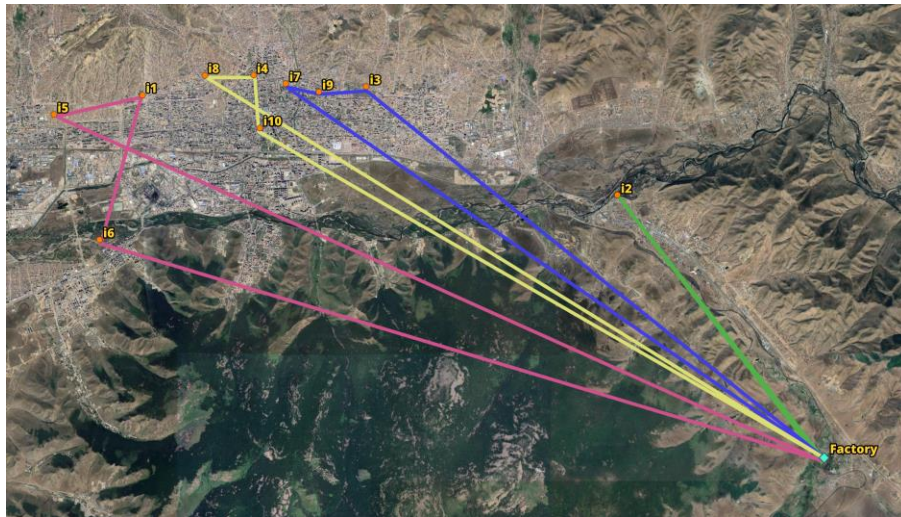


Figure 4.5 Period 2 (Peak Demand): 4 vehicles utilized

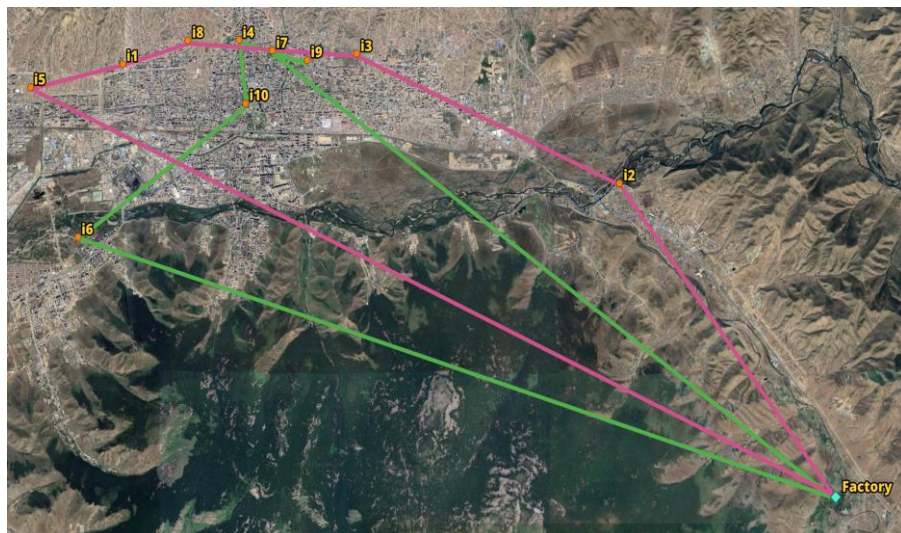


Figure 4.6 Period 6 (Low Demand): 2 vehicles utilized

Collectively, Figures 4.4-4.6 demonstrate the adaptive nature of the proposed routing framework. The number of active vehicles varies from two to four, depending on demand conditions, indicating that routing decisions are coordinated with production and demand

planning. This flexibility enables the system to maintain service levels while avoiding unnecessary transportation resources and costs.

Table 4.7 Vehicle usage by period

Period	Vehicles Used
t0	-
t1	k1, k2, k3
t2	k1, k2, k3, k4
t3	k1, k3, k4
t4	k1, k3, k4
t5	k1, k3, k4
t6	k1, k2
t7	k1, k4

The routing decisions presented in Table 4.6 are further supported by the vehicle utilization results reported in Table 4.7. The number of active vehicles decreases from four vehicles in periods t2 to only two vehicles in periods t6 and t7. This reduction reflects the declining delivery requirements observed toward the end of the planning horizon. The cost implications of this fleet consolidation can be observed in Appendix Table B.5, where total fixed vehicle costs decrease from 140,000 Tugriks in periods t2 and t3 to 70,000 Tugriks in periods t6 and t7. A similar pattern is evident in the variable routing costs shown in Appendix Table B.6. Routing expenditures decline from 224,515.20 Tugriks to 140,192.00 Tugriks in later period, indicating that lower demand volumes allow more efficient route consolidation.

Table 4.8 CO₂ emissions generated by vehicle routes

Period	Vehicle k1	Vehicle k2	Vehicle k3	Vehicle k4	Total CO ₂
t1	49.92	29.38	49.88	—	129.18
t2	52.89	43.77	18.75	38.95	154.36
t3	46.42	—	48.61	48.32	143.35
t4	55.16	—	41.36	29.38	125.9
t5	55.16	—	29.38	41.36	125.9
t6	59.47	37.49	—	—	96.96
t7	47.5	—	—	48.88	96.38
Total	366.52	110.64	188.98	206.89	872.03

The distribution of transportation-related emissions across planning periods is reported in Table 4.8. The highest emissions occur during periods t2 and t3 (154.36 kg CO₂), corresponding to the periods with the greatest vehicle utilization and routing activity. In contrast, emissions decline to approximately 96 kg CO₂ during periods t6 and t7 when only two vehicles are deployed. This finding confirms the close relationship between routing intensity and environmental performance within the integrated planning framework.

Service quality remained high throughout the planning horizon. As shown in Appendix Table B.9, no lateness is observed for the majority of retailer-period combinations. Only a small number of late deliveries occur in periods t6 and t7, and the associated lateness values remain

relatively limited. These results suggest that the routing plans satisfy retailer time-window requirements effectively while maintaining operational efficiency.

4.2 Sensitivity Analysis

The selected parameters for sensitivity analysis, DRO confidence level, ε -constraint for emission targets, vehicle capacity, and emission factor, represent the most critical sources of uncertainty, policy control, and operational constraints within the model. The DRO parameter captures demand uncertainty and risk aversion, the ε -constraint reflects environmental regulation strictness, vehicle capacity represents key logistical limitations, and the emission factor accounts for environmental impact intensity, making these parameters essential for evaluating the model's responsiveness and managerial relevance.

4.2.1 Sensitivity Analysis on DRO level

Table 4.9 Sensitivity analysis of the DRO parameter ε

ε DRO	Confidence	Cost (₺)	Emissions (kg CO ₂)
0.05	0.95	39.16M	926.92
0.25	0.75	30.38M	812.10
0.50	0.50	27.93M	732.21
0.75	0.25	26.48M	693.95
0.95	0.05	25.39M	693.95

The results reported in Table 4.9 demonstrate the impact of the DRO parameter ε on the economic and environmental performance of the proposed model. Lower values of ε correspond to higher confidence levels and more conservative ambiguity sets, requiring the model to remain feasible under a broader range of demand realizations. As a result, both total cost and CO₂ emissions attain their highest levels when $\varepsilon = 0.05$.

As ε increases, the ambiguity sets become less restrictive and the level of conservatism decreases. Consequently, the model is able to identify less costly procurement, production, inventory, and routing plans. Total cost decreases steadily from 39.16 million Tugriks at $\varepsilon = 0.05$ to 25.39 million Tugriks at $\varepsilon = 0.95$, representing a reduction of approximately 35%. A similar pattern is observed for transportation-related emissions, which decline from 926.92 kg CO₂ to 693.95 kg CO₂.

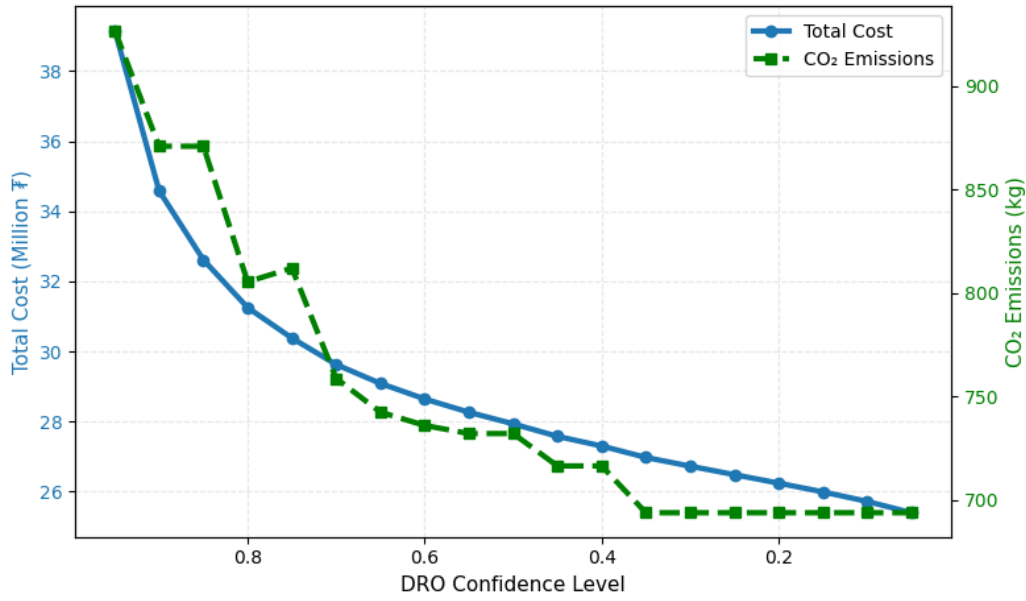


Figure 4.7 Sensitivity Analysis of DRO Confidence Level

Figure 4.7 illustrates the impact of the DRO confidence level on both total supply chain cost and transportation-related CO₂ emissions. As the confidence level increases, the model adopts more conservative decisions to remain feasible under a wider range of demand realizations, resulting in higher costs and emissions. Conversely, lower confidence levels allow the model to identify less conservative and more economical solutions. Both performance measures exhibit a decreasing trend as the confidence level is reduced, although the rate of improvement gradually diminishes. In particular, CO₂ emissions stabilize at lower confidence levels, indicating that further relaxation of the ambiguity set has limited influence on routing decisions. Overall, the results highlight the trade-off between robustness and operational efficiency, where greater protection against demand uncertainty requires additional economic and environmental resources.

4.2.2 Sensitivity Analysis on Emission Target

Table 4.10 Sensitivity analysis of the ε -constraint parameter

ε (%)	Cost (₹)	Emission (kg CO ₂)	Gap (%)	Run time (s)
0	43,766,848.07	838.11	11.17	2924.66
2	39,633,985.30	854.78	2.01	996.25
4	39,156,136.87	870.62	0.89	5.92
7	39,070,255.67	889.19	0.82	1.69
12	39,070,255.67	889.19	0.99	0.63
19	39,070,255.67	889.19	0.98	0.54

The results reported in Table 4.10 illustrate the effect of progressively relaxing the emission constraint within the ε -constraint framework. When $\varepsilon = 0\%$, the model is required to operate at the minimum achievable emission level of 838.11 kg CO₂, resulting in the highest total cost of 43.77 million Tugriks. This indicates that strict environmental requirements impose a substantial economic burden on the supply chain.

As the emission limit is gradually relaxed, total cost decreases rapidly while emissions increase only moderately. The most significant changes occur between $\varepsilon = 0\%$ and $\varepsilon = 4\%$, where total

cost is reduced by approximately 4.61 million Tugriks while emissions increase by only 32.51 kg CO₂. This region therefore represents the strongest trade-off between economic and environmental performance.

Beyond $\varepsilon \approx 7\%$, both total cost and emissions remain unchanged despite further increases in the ε parameter. The detailed results presented in Appendix C indicate that the same solution is obtained for all ε values from 7% to 19%, suggesting that the corresponding emission constraint is no longer binding. Consequently, additional relaxation of the environmental target does not affect procurement, production, inventory, or routing decisions.

A similar pattern is observed in computational performance. The runtime decreases from 2,924.66 seconds at $\varepsilon = 0\%$ to less than one second for several higher ε values, indicating that stricter environmental constraints substantially increase problem difficulty. These findings suggest that most economically meaningful improvements are achieved within a relatively narrow range of ε values, while larger relaxations provide limited additional benefit. The complete set of results is reported in Appendix C, Table C.2.

4.2.3 Sensitivity Analysis on Vehicle Capacity

Table 4.11 Sensitivity Analysis of Vehicle Capacity on Total Cost, Carbon Emissions

Capacity	Cost	Emission
80%	38,736,374	715.95
100%	38,636,470	675.21
120%	38,698,986	658.6

Table 4.12 Impact of Vehicle Capacity on Transportation Distance and Distribution Costs

Capacity	Distance	Vehicle Fixed Cost	Vehicle Variable Cost	Lateness Cost
80%	1301 km	525,000	1,041,383	128,100
100%	1227 km	455,000	982,124	157,455
120%	1197 km	455,000	957,964	244,130

The results reported in Tables 4.11 and 4.12 indicate that vehicle capacity has a significant influence on routing efficiency, transportation costs, and service performance. As vehicle capacity increases from 80% to 120% of the baseline level, total travel distance decreases from 1,301 km to 1,197 km, representing an 8.0% reduction. This improvement suggests that larger vehicle capacities enable greater shipment consolidation and reduce the need for additional vehicle trips.

The reduction in travel distance is accompanied by a decrease in vehicle variable transportation costs, which decline from 1,041,383 Tugriks at 80% capacity to 957,964 Tugriks at 120% capacity. Vehicle fixed costs also decrease when capacity increases from 80% to 100%, reflecting a lower number of vehicles required to satisfy customer demand. As a result, total emissions decrease steadily from 715.95 kg CO₂ to 658.60 kg CO₂, indicating that improved vehicle utilization contributes to environmental performance.

A different pattern is observed for service-related costs. Although transportation efficiency improves with larger vehicle capacities, lateness costs increase substantially, rising from 128,100 Tugriks at 80% capacity to 244,130 Tugriks at 120% capacity. This increase suggests

that highly consolidated routes may require vehicles to serve a larger number of retailers during a single tour, resulting in longer route durations and a higher risk of violating delivery time windows.

The effect of vehicle capacity on total supply chain cost is comparatively modest. The lowest total cost is achieved at the baseline capacity level (100%), while further capacity expansion provides only limited economic benefits despite reducing transportation distance and emissions. These findings indicate that increasing vehicle capacity improves transportation efficiency but may adversely affect service performance. Within the examined range, the baseline capacity level provides the most balanced solution by maintaining low total cost while avoiding excessive lateness penalties.

4.2.4 Sensitivity Analysis on Emission Factor

Table 4.13 Impact of Emission Factor on Total Cost and Emission

Emission Factor	Cost (€)	Emission
80%	39,201,538	703.74
100%	39,201,538	879.67
120%	No feasible solution	

The results presented in Table 4.13 show that increasing the emission factor from 80% to 100% raises total transportation-related emissions from 703.74 kg CO₂ to 879.67 kg CO₂. Since the emission factor directly determines the amount of CO₂ generated per unit distance traveled, this behavior is consistent with the model formulation. The corresponding total cost remains unchanged because the emission factor does not affect procurement, production, inventory, or routing costs.

A more significant observation is obtained at the 120% emission factor level, where no feasible solution exists. Under this scenario, the increased emission intensity causes total emissions to exceed the maximum allowable level imposed by the ε -constraint. Consequently, no routing and production plan can simultaneously satisfy all operational and environmental requirements. This finding indicates that the feasibility of the supply chain is sensitive to vehicle emission intensity and that sufficiently high emission factors may render the planning problem infeasible.

The analysis therefore highlights the importance of environmental parameters within the optimization framework. While changes in the emission factor do not alter economic performance directly, they can substantially influence environmental outcomes and, beyond a certain threshold, determine whether a feasible solution exists.

5. Conclusion

5.1 Answers to the main questions of the thesis

How can the ISSPRP proposed by (Hashemi-Amiri et al., 2023) be extended to better represent the operational characteristics of PFSCs under demand uncertainty, and how can the resulting EIPAPPRP be applied to support integrated planning decisions in a real-world SMEs food manufacturing enterprise?

Building on the ISSPRP proposed by (Hashemi-Amiri et al., 2023), this study developed an enhanced integrated procurement, production, inventory, and routing model tailored to the challenges of perishable food supply chains operating under demand uncertainty. The resulting EIPAPPRP incorporates transportation-related CO₂ emissions, retailer time-window constraints, perishability considerations, and a DRO framework for demand uncertainty. In addition, the model integrates procurement, production, inventory, and vehicle routing decisions within a single optimization framework, enabling coordinated planning across multiple supply chain functions.

The applicability of the proposed model was evaluated using operational data obtained from a Mongolian small and medium-sized ready-to-eat food manufacturer. The case study demonstrated that the EIPAPPRP can generate feasible and coordinated plans for procurement, production, inventory management, and distribution under uncertain demand conditions. The computational results confirmed that the model is capable of capturing the interactions among these decisions while satisfying operational constraints related to supplier capacities, production capacity, inventory management, vehicle availability, and retailer delivery requirements.

The results further showed that the proposed framework can support integrated planning decisions while balancing economic and environmental objectives. The multi-objective analysis revealed a clear trade-off between total supply chain cost and transportation-related CO₂ emissions, indicating that moderate environmental targets can be achieved without substantial increases in operational cost. The sensitivity analyses demonstrated the influence of uncertainty levels, vehicle capacities, and emission-related parameters on system performance, providing additional insights into the robustness and practical applicability of the model.

Therefore, the research question can be answered affirmatively. The proposed EIPAPPRP successfully extends the original ISSPRP to better reflect the operational realities of perishable food supply chains under demand uncertainty. Furthermore, its application to a real-world SMEs food manufacturing enterprise demonstrates its potential as a practical decision-support tool for integrated supply chain planning, enabling decision-makers to improve coordination, maintain operational feasibility, and incorporate sustainability considerations into planning decisions.

5.2 Research Limitations

Despite the contributions of this study, several limitations should be recognized.

First, the proposed model represents demand uncertainty through a DRO framework with predefined ambiguity sets constructed from eight weeks of historical demand observations for each retailer-product combination. Although this approach improves robustness compared with deterministic formulations and captures recent demand patterns, the limited amount of historical data may not fully reflect seasonal effects, long-term demand trends, or structural changes in customer behavior. Consequently, the estimated ambiguity sets may not represent the complete range of future demand conditions. Furthermore, the choice of DRO parameters, particularly the confidence level, influences the degree of conservatism in the resulting solutions and may lead to decisions that are more cautious than necessary under certain operating conditions.

Second, the production system is modeled using an aggregated capacity representation rather than a detailed production scheduling framework. While this assumption is consistent with the planning practices of many small and medium-sized food manufacturers, it does not explicitly account for machine-level constraints, setup times, sequencing decisions, or workforce-related considerations. These factors may become important in more complex production environments.

Third, the environmental assessment focuses exclusively on transportation-related CO₂ emissions. Other emission sources, including raw material production, food processing, cold-storage, packaging, and product waste, were excluded from the analysis due to data limitations and the lack of detailed emission information at the operational level. As a result, the environmental performance evaluated by the model reflects only the transportation component of the supply chain and does not capture the full carbon footprint associated with food production and distribution.

Another limitation arises from the assumption that most model parameters, including costs, processing times, and emission coefficients, are deterministic. Demand uncertainty is explicitly incorporated through the DRO framework; however, other sources of uncertainty, such as supplier reliability, transportation times, fuel consumption, and operational disruptions, are not considered. Incorporating these uncertainties could lead to a more comprehensive representation of real-world supply chain conditions.

Finally, the model was validated using data from a single Mongolian SMEs ready-to-eat food manufacturer. Although the case study provides valuable practical insights and demonstrates the applicability of the proposed framework, the findings may not be directly generalizable to other companies, industries, or geographical regions with different supply chain structures and operational characteristics.

5.3 Future Recommendations

Future research can extend the proposed model in several directions. While demand uncertainty is incorporated through the DRO framework, future studies could consider additional sources of uncertainty, such as supplier disruptions, transportation delays, fuel price fluctuations, and variations in processing times. Incorporating multiple uncertainty sources would provide a more realistic representation of food supply chain operations and allow a broader assessment of supply chain resilience.

The production component of the model could also be refined by integrating detailed production planning features, including machine-level capacities, setup times, sequence-

dependent operations, and workforce considerations. Such extensions would enable the model to capture operational complexities that are particularly relevant in larger or more technologically advanced manufacturing environments.

Another promising direction is the incorporation of more advanced perishability and product deterioration models. In the current study, perishability is represented through shelf-life constraints and inventory-related considerations. However, the quality of food products often deteriorates gradually over time and can be influenced by factors such as storage conditions, transportation duration, and temperature fluctuations. Integrating dynamic deterioration rates, quality decay functions, or temperature-dependent shelf-life models would provide a more realistic representation of perishable food supply chains and support more effective decisions regarding production, inventory management, and distribution planning.

Future studies could also develop a more comprehensive environmental assessment by including emissions generated during raw material production, manufacturing processes, refrigeration and storage activities, packaging, and food waste management. This would allow the evaluation of the entire supply chain carbon footprint rather than focusing solely on transportation-related emissions.

Furthermore, the model could be validated using data from multiple food manufacturing companies and different product categories. Applying the framework across various operational settings would improve the generalizability of the findings and provide further insights into the applicability of DRO in small and medium-sized food manufacturing enterprises.

5.4 Managerial Insights

The results suggest that effective management of perishable food supply chains requires coordinated decision-making across procurement, production, and distribution activities. Since these functions are closely interconnected, decisions made in one area directly influence the performance of the others. The integrated planning framework helps improve overall efficiency by considering these interactions simultaneously.

The analysis also highlights the importance of balancing robustness, cost, and sustainability objectives. Very conservative decisions under uncertainty increase operational costs, while overly strict emission limits may impose substantial economic burdens. The results indicate that moderate levels of robustness and environmental restrictions can provide a more practical balance between economic and environmental performance.

The transportation-related results show that logistics efficiency cannot be improved simply by increasing vehicle capacity or focusing on a single performance measure. While larger vehicle capacities can reduce transportation requirements and emissions, they may also affect service performance. Similarly, environmentally efficient transportation practices contribute not only to sustainability goals but also to maintaining feasible operations under environmental constraints.

Taken together, the findings demonstrate that successful management of perishable food supply chains depends on balancing economic, environmental, and operational objectives. The proposed framework provides a practical decision-support tool for evaluating these trade-offs and supporting integrated planning under uncertainty.

Appendix A. Supplementary data for the case study problem

Table A.1 The travel time between cold-storage and retailers in minutes

		Cold-storage	Retailer 1	Retailer 2	Retailer 3	Retailer 4	Retailer 5	Retailer 6	Retailer 7	Retailer 8	Retailer 9	Retailer 10
		i0	i1	i2	i3	i4	i5	i6	i7	i8	i9	i10
Cold-storage	i0	0	61	26	47	56	67	61	55	58	54	53
Retailer 1	i1	61	0	41	18	8.9	8.4	12	11	4.7	9.8	9.5
Retailer 2	i2	26	41	0	9.5	30	41	35	29	33	28	27
Retailer 3	i3	47	18	9.5	0	9.9	25	30	7.7	13	5.9	8.9
Retailer 4	i4	56	8.9	30	9.9	0	19	15	2.8	7.7	2.7	3.4
Retailer 5	i5	67	8.4	41	25	19	0	14	18	10	17	14
Retailer 6	i6	61	12	35	30	15	14	0	16	14	15	14
Retailer 7	i7	55	11	29	7.7	2.8	18	16	0	8.4	1.4	4.3
Retailer 8	i8	58	4.7	33	13	7.7	10	14	8.4	0	6.7	9.3
Retailer 9	i9	54	9.8	28	5.9	2.7	17	15	1.4	6.7	0	3
Retailer 10	i10	53	9.5	27	8.9	3.4	14	14	4.3	9.3	3	0

Table A.1 reports the travel times between the cold-storage facility and retailers and among retailers within the distribution network. The travel times are measured in minutes and serve as input parameters for the vehicle routing problem. These data are used to determine feasible delivery routes, and calculate vehicle arrival times.

Table A.2 Supplier, Raw Material Parameters and Inbound Transportation Costs

Supplier	Raw material	Unit	Availability	Capacity	Unit purchasing cost	Inbound transport cost
q1	r1 (Rice)	kg	1	100	3,536.17	200
q1	r7 (Vegetable mix)	kg	1	40	3,770.37	200
q1	r8 (Soya sauce)	litre	1	14	5,262.11	250
q1	r9 (Beef tenderloin)	kg	1	45	15,738.11	200
q2	r1 (Rice)	kg	1	70	3,728.39	200
q2	r2 (Oil)	litre	1	13	21,253.91	250
q2	r3 (Spices)	kg	1	14	18,240.25	200
q3	r4 (Chicken meat)	kg	1	25	14,742.99	200
q3	r5 (Tuna)	kg	1	24	23,026.24	200
q3	r6 (Seaweed pcs)	pcs	1	1,200	277.68	5
q3	r10 (Plastic roll pcs)	pcs	1	715	176.61	5
q4	r2 (Oil)	litre	1	7	19,504.35	250
q4	r6 (Seaweed pcs)	pcs	1	700	295.26	5
q4	r8 (Soya sauce)	litre	1	16	5,163.41	250
q4	r10 (Plastic roll pcs)	pcs	1	1,250	199.43	5
q5	r3 (Spices)	kg	1	10	17,050.06	200
q5	r4 (Chicken meat)	kg	1	18	15,738.11	200
q5	r5 (Tuna)	kg	1	16	22,406.44	200
q5	r7 (Vegetable mix)	kg	1	30	4,049.41	200
q5	r9 (Beef tenderloin)	kg	1	35	14,742.99	200

Table A.2 presents the supplier-related parameters used in the procurement component of the model, including raw material availability, supplier capacities, unit purchasing costs, and inbound transportation costs. These data serve as key inputs for procurement planning and supplier selection decisions. The parameters influence the allocation of raw material orders among suppliers while satisfying material requirements and capacity constraints at minimum procurement and transportation cost.

Table A.3 BOM Coefficients

Raw material	Product n1	Product n2	Product n3
r1 (Rice)	0.081	0.04762	0.04762
r2 (Oil)	0.012	0.01018	0.01010
r3 (Spices)	0.0058	0.0034	0.0036
r4 (Chicken meat)	-	0.0412	-
r5 (Tuna)	-	-	0.05125
r6 (Seaweed pcs)	1	1	1
r7 (Vegetable mix)	0.072	-	-
r8 (Soya sauce)	-	0.015	0.015
r9 (Beef tenderloin)	0.07004	-	-
r10 (Plastic roll pcs)	1	1	1

Table A.3 reports the BOM coefficients used in the model. The coefficients specify the amount of each raw material required to produce one unit of each finished product and serve as key input parameters in the production planning process. They are used to calculate raw material requirements and link procurement decisions with production activities throughout the planning horizon.

Table A.4 Production and Storage Capacity Parameters

Parameter	Description	Value (units)
Cap^{prod}	Aggregate daily production capacity	5,000
Cap^{stor}	Maximum cold-storage capacity	25,500

Table A.4 presents the production and storage capacity parameters used in the case study. These parameters define the maximum production volume and cold-storage capacity available during each planning period. They serve as operational constraints in the model, ensuring that production and inventory decisions remain within the available facility resources.

Table A.5 Retailer Service Times

Retailer	Service time (minutes)
i1	12
i2	16
i3	13
i4	20
i5	17
i6	14
i7	16
i8	19
i9	12
i10	16

Table A.5 presents the service times required at each retailer during product delivery operations. Service time represents the duration needed for unloading, handling, and completing delivery activities at the retailer location. These parameters are incorporated into

the vehicle routing model to ensure realistic route schedules and compliance with delivery time constraints.

Table A.6 Vehicle Fleet Characteristics

Vehicle	Capacity (kg)	Fixed cost (₹)	Variable cost (₹/km)
k1	500	35,000	800
k2	500	35,000	800
k3	500	35,000	800
k4	500	35,000	800

Table A.6 summarizes the characteristics of the vehicle fleet used for product distribution. For each vehicle, the table reports the available carrying capacity, fixed operating cost, and distance-based transportation cost. These parameters are used in the vehicle routing component of the model to determine vehicle utilization, transportation costs, and distribution plans across the planning horizon.

Table A.7 Goodwill Loss Parameter

Parameter	Description	Value (₹)
GL	Goodwill loss per unit time for service violation	2,500

Table A.7 presents the goodwill loss parameter used to quantify the penalty associated with service-level violations. The parameter represents the economic impact of delayed deliveries and customer dissatisfaction, expressed as a cost per unit of lateness. It is incorporated into the objective function to encourage timely deliveries and maintain customer service performance.

Table A.8 Product related parameters

Parameter		n1	n2	n3
Product unit weight (kg/unit)	w_n	0.67926	0.39396	0.409215
Inventory cost	h_n	200	150	150
Production cost	c_n^{prod}	300	250	250
Storage Deterioration Beta	β_n	0.035	0.025	0.025

Table A.8 summarizes the product-specific parameters used in the model for the three finished products. The table reports unit weight, inventory holding cost, and deterioration rate parameters for each product. These parameters are incorporated into the production, inventory, and distribution components of the model and influence storage decisions, vehicle usage, transportation requirements, inventory costs, and product quality preservation throughout the planning horizon.

Table A.9 Global Model Parameters

Parameter	Description	Value	Unit
$U_{\max}$	Maximum allowable route duration	11	hours
$T^{\max}$	Big-M parameter used in routing time constraints	1,000	minutes
ε	DRO parameter	0.05	-
e	Transportation CO ₂ emission factor	0.55	kg CO ₂ /km

Table A.9 presents the global parameters applied throughout the optimization model. These parameters define key operational, environmental, and modeling settings, including the

maximum route duration, the Big-M value used in time-related constraints, the DRO risk tolerance level, and the transportation emission factor. They are used across multiple model components and influence routing feasibility, uncertainty handling, and environmental performance evaluation.

Table A.10 The complete set of distributionally robust demand thresholds

Retailer	Product	t1	t2	t3	t4	t5	t6	t7
i1	n1	107.57	90.35	92.58	93.32	88.50	68.60	56.75
i1	n2	91.51	93.63	91.11	88.68	76.08	75.97	72.71
i1	n3	69.20	75.08	75.25	75.31	70.08	50.13	35.62
i2	n1	81.69	102.07	99.42	84.48	69.23	65.58	57.19
i2	n2	68.72	76.42	60.39	64.52	65.63	49.87	42.55
i2	n3	63.79	74.47	75.61	73.69	66.76	52.36	39.37
i3	n1	101.38	108.61	115.67	77.97	79.68	72.00	62.41
i3	n2	88.14	85.79	93.67	67.57	67.27	66.20	68.30
i3	n3	72.99	76.91	78.79	67.20	65.55	44.03	43.12
i4	n1	72.36	77.27	80.72	97.03	75.08	77.49	63.29
i4	n2	78.94	86.18	101.26	86.79	72.72	61.19	59.67
i4	n3	69.45	103.02	77.21	70.20	59.79	43.55	42.94
i5	n1	80.11	84.20	94.78	91.44	81.42	67.38	53.69
i5	n2	81.65	85.01	85.22	79.26	70.11	54.43	57.84
i5	n3	63.75	64.27	79.34	65.06	64.76	49.56	44.86
i6	n1	86.60	99.33	90.17	89.58	74.68	62.93	58.18
i6	n2	72.72	89.85	66.62	82.79	57.60	46.91	64.38
i6	n3	75.26	69.41	89.38	74.31	64.15	47.60	36.23
i7	n1	99.26	104.43	92.23	104.31	90.41	75.13	59.49
i7	n2	92.73	93.98	98.91	91.62	81.88	60.10	61.85
i7	n3	69.45	67.62	82.88	64.27	59.14	55.79	47.39
i8	n1	90.70	94.61	104.55	89.51	97.38	78.10	58.44
i8	n2	69.76	86.74	81.25	82.47	71.20	54.48	56.84
i8	n3	70.20	68.32	76.12	80.05	63.31	46.21	44.51
i9	n1	106.17	101.28	91.14	91.27	90.72	74.44	56.56
i9	n2	91.59	83.17	89.71	76.16	79.75	53.79	53.18
i9	n3	79.84	84.71	81.44	63.10	74.35	50.44	40.37
i10	n1	87.08	89.47	83.19	84.02	77.54	60.79	61.15
i10	n2	89.97	81.08	77.86	66.32	73.11	54.09	47.34
i10	n3	82.28	93.82	86.76	70.68	61.49	57.37	47.91

Table A.10 reports the complete set of distributionally robust demand thresholds $U_{i,n,t}^\delta$ for all retailer-product-period combinations. The values are calculated using the historical demand mean and standard deviation according to $U_{i,n,t}^\delta = \mu_{i,n,t} + \sqrt{\frac{1-\varepsilon}{\varepsilon}} \sigma_{i,n,t}$. These thresholds represent the robust demand estimates used in the demand satisfaction constraints and serve as key inputs to the production, inventory, and distribution planning decisions.

Table A.11 Raw material initial inventory

Material	Initial Inventory
r1	0
r2	0
r3	0
r4	0
r5	0
r6	0
r7	0
r8	0
r9	0
r10	0

Table A.11 reports the initial inventory levels of raw materials used in the model. All initial inventories are assumed to be zero, indicating that no raw material stock is available at the start of the planning horizon and that procurement decisions are required to satisfy production requirements.

Table A.12 Raw material holding cost

Material	Holding Cost
r1	25
r2	14
r3	25
r4	30
r5	17
r6	15
r7	15
r8	16
r9	10
r10	18

Table A.12 reports the holding costs assigned to each raw material. These costs represent the expense of carrying raw material inventory between planning periods and are incorporated into the economic objective function through the raw material inventory variables. The parameters influence procurement timing and inventory decisions by balancing material availability against inventory-related costs.

Appendix B. The detailed results of the case study problem and sensitivity analyses ($\varepsilon = 5\%$)

Procurement decisions

Table B.1 Detailed procurement decisions (Period t0 - t7)

Period	Supplier	Raw Material	Quantity	Cost (Tugriks)
Period t0	q1	r1	7.5	28,012.94
	q1	r7	50	198,518.50
	q3	r4	25	373,574.75
	q3	r6	454.63	128,514.81
	q3	r10	1054.63	191,531.36
	q4	r8	15.26	82,628.29
	q5	r3	3.61	62,337.43
	q5	r9	35	523,004.65
Total procurement t0 cost				1,588,122.74
Period t1	q1	r1	150	560,425.50
	q1	r7	50	198,518.50
	q3	r4	25	373,574.75
	q3	r5	36.7	852,464.57
	q3	r6	2000	565,360.00
	q3	r10	1400	254,254.00
	q4	r2	26.69	524,526.26
	q4	r8	20	108,268.20
	q5	r3	10	172,500.60
	q5	r9	35	523,004.65
Total procurement t1 cost				4,132,897.03
Period t2	q1	r1	150	560,425.50
	q1	r7	50	198,518.50
	q1	r9	25.58	407,690.27
	q3	r4	25	373,574.75
	q3	r5	39.85	925,550.97
	q3	r6	2000	565,360.00
	q3	r10	1400	254,254.00
	q4	r2	28	550,321.80
	q4	r6	590.84	177,405.45
	q4	r8	20	108,268.20
	q4	r10	1190.84	243,443.31
	q5	r3	10	172,500.60
	q5	r9	35	523,004.65

Total procurement t2 cost				5,060,317.99
Period t3	q1	r1	150	560,425.50
	q1	r7	50	198,518.50
	q1	r9	31.14	496,358.04
	q3	r4	25	373,574.75
	q3	r5	41.14	955,495.21
	q3	r6	2000	565,360.00
	q3	r10	1400	254,254.00
	q4	r2	28	550,321.80
	q4	r6	592.98	178,047.44
	q4	r8	20	108,268.20
	q4	r10	1192.98	243,880.40
	q5	r3	10	172,500.60
	q5	r4	4.37	98,861.56
	q5	r7	2.23	9,465.61
	q5	r9	35	523,004.65
Total procurement t3 cost				5,288,336.26
Period t4	q1	r1	144.08	538,301.04
	q1	r7	50	198,518.50
	q1	r9	28.23	450,011.64
	q3	r4	25	373,574.75
	q3	r5	36.07	837,750.18
	q3	r6	2000	565,360.00
	q3	r10	1400	254,254.00
	q4	r2	25.94	509,928.01
	q4	r6	392.72	117,919.15
	q4	r8	20	108,268.20
	q4	r10	992.72	202,942.46
	q5	r3	10	172,500.60
	q5	r4	7.39	166,996.54
	q5	r7	15	63,760.32
	q5	r9	35	523,004.65
Total procurement t4 cost				5,083,090.04
Period t5	q1	r1	131.77	492,324.90
	q1	r7	50	198,518.50
	q1	r9	22.75	362,622.62
	q3	r4	25	373,574.75
	q3	r5	33.28	772,934.87
	q3	r6	2000	565,360.00

	q3	r10	1400	254,254.00
	q4	r2	23.73	466,488.84
	q4	r6	189.18	56,804.31
	q4	r8	20	108,268.20
	q4	r10	789.18	161,332.83
	q5	r3	9.55	164,773.04
	q5	r4	4.47	101,050.10
	q5	r7	9.37	39,808.69
	q5	r9	35	523,004.65
Total procurement t5 cost				4,641,120.31
Period t6	q1	r1	108.04	403,639.81
	q1	r7	50	198,518.50
	q1	r9	14.19	226,227.71
	q3	r4	23.77	355,223.86
	q3	r5	25.47	591,607.31
	q3	r6	1776.37	502,143.10
	q3	r10	1400	254,254.00
	q4	r2	19.32	379,760.58
	q4	r8	16.11	87,209.53
	q4	r10	376.37	76,940.47
	q5	r3	7.82	134,977.20
	q5	r7	0.57	2,425.50
	q5	r9	35	523,004.65
Total procurement t6 cost				3,735,932.22
Period t7	q1	r1	95.5	356,821.02
	q1	r7	42.27	167,833.54
	q1	r9	6.12	97,553.77
	q3	r4	24.09	359,916.77
	q3	r5	21.64	502,680.54
	q3	r6	1594.01	450,595.90
	q3	r10	1400	254,254.00
	q4	r2	17.26	339,269.65
	q4	r8	15.1	81,762.23
	q4	r10	194.01	39,662.30
	q5	r3	6.91	119,252.39
	q5	r9	35	523,004.65
Total procurement t7 cost				3,292,606.77

Table B.1 presents the detailed procurement decisions for all planning periods (t0-t7) under the baseline scenario ($\varepsilon = 5\%$). The table reports the selected suppliers, purchased raw materials,

procurement quantities, and corresponding procurement costs in each period. Period-specific total procurement costs are also provided.

Production results

Table B.2 Detailed production quantities by period

	Product	Production Quantity	Production Cost (Tugriks)
Period 1	n1	912.82	273,847.46
	n2	825.66	206,413.97
	n3	716.15	179,037.32
Period 2	n1	951.53	285,459.74
	n2	861.76	215,439.59
	n3	777.55	194,387.16
Period 3	n1	944.36	283,307.43
	n2	845.91	211,478.72
	n3	802.7	200,676.14
Period 4	n1	902.84	270,852.13
	n2	786.1	196,523.80
	n3	703.79	175,946.96
Period 5	n1	824.56	247,366.88
	n2	715.29	178,822.63
	n3	649.34	162,334.24
Period 6	n1	702.37	210,711.61
	n2	576.99	144,247.21
	n3	497	124,251.25
Period 7	n1	587.1	176,131.30
	n2	584.61	146,152.88
	n3	422.3	105,574.57
	Total	15,590.73	4,188,962.99

Table B.2 reports the optimal production quantities and associated production costs for each product in each period under the baseline scenario ($\epsilon = 5\%$). The final row summarizes the total production volume and total production cost across all periods.

Raw Material Inventory

Table B.3 Raw material inventory holding cost period t0-t7

Period	Total Holding Cost (Tugriks)
t0	28,174.79
t1	1,576.62
t2	689.47
t3	56.15
t4	7.51
t5-t7	0
Total	30,504.54

Table B.3 presents the raw material inventory holding costs generated by the optimal solution in each planning period under the baseline scenario ($\epsilon = 5\%$). The total holding cost across all periods is also reported.

Table B.4 Detailed Raw material inventory and holding cost by period

	Raw Material	Inventory Level	Holding Cost (Tugriks)
Period t0	r1	7.5	187.44
	r3	3.61	90.34
	r4	25	750
	r6	454.63	6,819.45
	r7	50	750
	r8	15.26	244.22
	r9	35	350
	r10	1054.63	18,983.34
Period t1	r1	10.14	253.45
	r2	0.1	1.34
	r3	2.93	73.35
	r4	15.98	479.49
	r7	34.28	514.15
	r8	12.14	194.18
	r9	6.07	60.66
Period t2	r1	5	125.01
	r2	0.05	0.71
	r3	1.69	42.15
	r4	5.48	164.36
	r7	15.77	236.49
	r8	7.55	120.75
Period t3	r3	0.44	11.07
	r8	2.82	45.08
Period t4	r8	0.47	7.51
Period t5-t7	r1-r10	0	0

Table B.4 presents the detailed raw material inventory levels and the corresponding holding costs for each material across the planning periods under the baseline scenario ($\varepsilon = 5\%$). Only materials with positive inventory levels are reported, while periods with zero inventory indicate that all available raw materials were utilized in production.

Routing Decision Results

Table B.5 Fixed vehicle cost results by period

Period	Vehicles Used	Number of Vehicles	Fixed Cost per Vehicle (Tugriks)	Total Fixed Cost (Tugriks)
t1	k1, k2, k3	3	35,000	105,000
t2	k1, k2, k3, k4	4	35,000	140,000
t3	k1, k3, k4	3	35,000	105,000
t4	k1, k3, k4	3	35,000	105,000
t5	k1, k3, k4	3	35,000	105,000
t6	k1, k2	2	35,000	70,000
t7	k1, k4	2	35,000	70,000
Total	-	20 vehicle deployments	-	700,000

Table B.5 reports the utilization of the vehicle fleet and the associated fixed transportation costs across the planning periods under the baseline scenario ($\varepsilon = 5\%$). The total fixed cost in each period depends on the number of vehicles activated for distribution activities.

Table B.6 Vehicle variable routing cost results by period

Period	Variable Routing Cost (Tugriks)
t1	187,896.80
t2	224,515.20
t3	208,520.00
t4	183,123.20
t5	183,123.20
t6	141,034.40
t7	140,192.00
Total	1,268,404.80

Table B.6 reports the variable transportation costs incurred in each planning period under the baseline scenario ($\varepsilon = 5\%$). These costs are calculated based on the routing distances traveled by the vehicle fleet and reflect the distribution effort required to satisfy retailer demand throughout the planning horizon.

Table B.7 Delivery quantities of finished products to retailers by period

Period	Retailer	n1	n2	n3
t1	i1	107.56	91.5	69.19
	i2	81.68	68.71	63.79
	i3	101.37	88.13	72.99
	i4	72.35	78.94	69.45
	i5	80.1	81.64	63.74
	i6	86.59	72.72	75.25
	i7	99.25	92.72	69.45
	i8	90.69	69.75	70.19
	i9	106.16	91.58	79.83
	i10	87.07	89.96	82.27
t2	i1	90.35	93.62	75.07
	i2	102.06	76.41	74.46
	i3	108.6	85.78	76.9
	i4	77.27	86.17	103.01
	i5	84.19	85	64.26
	i6	99.32	89.84	69.4
	i7	104.42	93.97	67.62
	i8	94.6	86.73	68.31
	i9	101.27	83.17	84.7
	i10	89.46	81.07	93.81
t3	i1	92.57	91.1	75.24
	i2	99.41	60.38	75.6
	i3	115.66	93.66	78.78
	i4	80.71	101.25	77.21
	i5	94.78	85.21	79.34
	i6	90.17	66.62	89.37
	i7	92.22	98.89	82.87
	i8	104.54	81.25	76.11
	i9	91.13	89.7	81.43
	i10	83.18	77.85	86.75
t4	i1	93.31	88.67	75.3
	i2	84.47	64.52	73.69
	i3	77.97	67.56	67.19
	i4	97.02	86.78	70.19
	i5	91.43	79.25	65.05
	i6	89.57	82.78	74.3
	i7	104.3	91.61	64.26

	i8	89.5	82.46	80.04
	i9	91.26	76.15	63.09
	i10	84.01	66.31	70.67
t5	i1	88.49	76.08	70.07
	i2	69.22	65.62	66.76
	i3	79.68	67.26	65.54
	i4	75.07	72.72	59.79
	i5	81.42	70.1	64.76
	i6	74.67	57.6	64.15
	i7	90.4	81.87	59.13
	i8	97.37	71.19	63.31
	i9	90.71	79.74	74.34
	i10	77.54	73.1	61.49
t6	i1	68.59	75.96	50.13
	i2	65.58	49.86	52.35
	i3	71.99	66.2	44.03
	i4	77.48	61.19	43.55
	i5	67.37	54.43	49.56
	i6	62.93	46.9	47.6
	i7	75.13	60.1	55.79
	i8	78.09	54.48	46.2
	i9	74.43	53.79	50.44
	i10	60.79	54.09	57.36
t7	i1	56.75	72.7	35.62
	i2	57.18	42.55	39.37
	i3	62.4	68.3	43.12
	i4	63.28	59.67	42.94
	i5	53.69	57.83	44.86
	i6	58.18	64.37	36.23
	i7	59.49	61.85	47.38
	i8	58.44	56.84	44.51
	i9	56.56	53.18	40.37
	i10	61.14	47.33	47.91

Table B.7 reports the quantities of finished products delivered to each retailer across the planning horizon under the baseline scenario ($\varepsilon = 5\%$). These values reflect the optimal distribution plan determined by the integrated production-inventory-routing model.

Table B.8 *Arrival times of vehicles at retailers for each planning period*

Retailer	t1	t2	t3	t4	t5	t6	t7
i1	4.20E+02	4.20E+02	4.20E+02	4.20E+02	4.70E+02	5.05E+02	4.20E+02
i2	3.60E+02	4.20E+02	3.60E+02	3.92E+02	3.60E+02	3.60E+02	3.60E+02
i3	4.20E+02	4.20E+02	4.20E+02	4.20E+02	4.20E+02	4.51E+02	4.20E+02
i4	4.44E+02	4.50E+02	4.20E+02	4.56E+02	4.20E+02	4.20E+02	4.65E+02
i5	5.40E+02	5.40E+02	5.40E+02	5.72E+02	6.00E+02	6.00E+02	5.60E+02
i6	3.00E+02	3.00E+02	3.00E+02	3.27E+02	3.60E+02	3.60E+02	3.00E+02
i7	5.40E+02	6.00E+02	6.00E+02	6.00E+02	5.40E+02	6.00E+02	6.00E+02
i8	4.80E+02	4.80E+02	4.80E+02	5.40E+02	5.40E+02	4.80E+02	4.80E+02
i9	4.20E+02	4.41E+02	4.80E+02	4.80E+02	4.44E+02	4.80E+02	4.88E+02
i10	3.60E+02	3.60E+02	3.60E+02	3.60E+02	4.00E+02	4.00E+02	4.45E+02

Table B.8 presents the vehicle arrival times at each retailer across the planning horizon under the baseline scenario ($\varepsilon = 5\%$). The reported times reflect the routing and scheduling decisions generated by the optimization model and demonstrate the feasibility of the distribution plan with respect to service requirements.

Table B.9 *Lateness values at retailers for each planning period*

Retailer	t1	t2	t3	t4	t5	t6	t7
i1	0	0	0	0	0	2.51E+01	0
i2	0	0	0	0	0	0	0
i3	0	0	0	0	0	0	0
i4	0	0	0	0	0	0	0
i5	0	0	0	0	0	0	0
i6	0	0	0	0	0	0	0
i7	0	0	0	0	0	0	0
i8	0	0	0	0	0	0	0
i9	0	0	0	0	0	0	8.47E+00
i10	0	0	0	0	0	0	2.45E+01

Table B.9 reports the retailer lateness values generated by the optimal routing schedule under the baseline scenario ($\varepsilon = 5\%$). Most deliveries are completed within the required service windows, while limited lateness is observed only at a small number of retailers and periods.

Appendix C. The detailed results of the sensitivity analyses

DRO Sensitivity Analysis

Table C.1 Detailed sensitivity analysis of the DRO parameter ε

ε_{DRO}	G1	G2	Confidence	Cost (¥)	Emissions (kg CO ₂)
0.05	39,144,900.47	838.11	0.95	39,160,136.47	926.92
0.1	39,144,900.47	838.11	0.9	34,584,445.63	870.99
0.15	39,144,900.47	838.11	0.85	32,614,760.29	870.99
0.2	39,144,900.47	838.11	0.8	31,249,683.40	805.52
0.25	39,144,900.47	838.11	0.75	30,380,264.02	812.1
0.3	39,144,900.47	838.11	0.7	29,625,537.95	758.86
0.35	39,144,900.47	838.11	0.65	29,084,511.49	742.55
0.4	39,144,900.47	838.11	0.6	28,641,901.39	736.14
0.45	39,144,900.47	838.11	0.55	28,262,541.59	732.21
0.5	39,144,900.47	838.11	0.5	27,931,741.18	732.21
0.55	39,144,900.47	838.11	0.45	27,574,780.23	716.57
0.6	39,144,900.47	838.11	0.4	27,298,864.73	716.57
0.65	39,144,900.47	838.11	0.35	26,971,790.77	693.95
0.7	39,144,900.47	838.11	0.3	26,723,742.59	693.95
0.75	39,144,900.47	838.11	0.25	26,481,468.36	693.95
0.8	39,144,900.47	838.11	0.2	26,239,047.23	693.95
0.85	39,144,900.47	838.11	0.15	25,988,599.69	693.95
0.9	39,144,900.47	838.11	0.1	25,717,038.55	693.95
0.95	39,144,900.47	838.11	0.05	25,394,012.03	693.95

Table C.1 summarizes the impact of varying the DRO risk tolerance parameter ε on the model's performance. Lower values of ε correspond to higher confidence levels and more conservative decisions, resulting in higher costs and emissions. As ε increases and the confidence level decreases, both total cost and emissions gradually decline, illustrating the trade-off between robustness and operational efficiency.

E-Constraint Sensitivity Analysis

Table C.2 Detailed results of the ε -Constraint Sensitivity Analysis for Cost and Emission Objectives

ε (Epsilon)	G1	G2	Cost	Emission	Gap (%)	Run time (s)
0%	39,144,900.47	838.11	60,586,047.53	838.11	35.85	9,315.17
1%	39,144,900.47	838.11	43,832,147.87	844.63	11.27	4,981.45
2%	39,144,900.47	838.11	43,183,980.67	854.15	9.83	71,446.48
3%	39,144,900.47	838.11	42,999,884.67	861.37	9.42	6,545.30
4%	39,144,900.47	838.11	42,380,852.67	865.81	8.1	9,750.35
5%	39,144,900.47	838.11	39,158,185.67	872.03	0.78	225.54
6%	39,144,900.47	838.11	39,158,185.67	872.03	1	1.13
7%	39,144,900.47	838.11	39,158,185.67	872.03	1	1.26
8%	39,144,900.47	838.11	39,072,304.47	890.6	0.83	1.04
9%	39,144,900.47	838.11	39,072,304.47	890.6	1	0.33
10%	39,144,900.47	838.11	39,072,304.47	890.6	0.99	0.33
11%	39,144,900.47	838.11	39,072,304.47	890.6	0.99	0.32
12%	39,144,900.47	838.11	39,072,304.47	890.6	0.99	0.31
13%	39,144,900.47	838.11	39,072,304.47	890.6	1	0.55
14%	39,144,900.47	838.11	39,072,304.47	890.6	0.97	0.54
15%	39,144,900.47	838.11	39,072,304.47	890.6	1	0.33
16%	39,144,900.47	838.11	39,072,304.47	890.6	0.99	0.33
17%	39,144,900.47	838.11	39,072,304.47	890.6	0.99	0.34
18%	39,144,900.47	838.11	39,072,304.47	890.6	0.99	0.34
19%	39,144,900.47	838.11	39,072,304.47	890.6	0.99	0.34

Table C.2 reports the solutions obtained under different ε -constraint levels. The results demonstrate the existence of a trade-off between cost minimization and emission reduction. Stricter emission constraints lead to higher operating costs, while relaxing the emission limits allows lower-cost solutions at the expense of increased emissions. The relatively small optimality gaps indicate that high-quality solutions were obtained for all tested scenarios.

References

- Abad, P. L. (2003). Optimal pricing and lot-sizing under conditions of perishability, finite production and partial backordering and lost sale. *European Journal of Operational Research*, 144(3), 677–685. [https://doi.org/10.1016/S0377-2217\(02\)00159-5](https://doi.org/10.1016/S0377-2217(02)00159-5)
- Accorsi, R., Ferrari, E., Guidani, B., Manzini, R., & Ronzoni, M. (2025). An optimization framework for energy-driven food cold chain network design. *Journal of Cleaner Production*, 514, 145767. <https://doi.org/10.1016/j.jclepro.2025.145767>
- Acevedo-Ojeda, A., & Chen, M. (2020). Multi-level lot-sizing with raw-material perishability, deterioration, and batch ordering: An application of production planning in advanced composite manufacturing. *Computers & Industrial Engineering*, 145, 106484. <https://doi.org/10.1016/j.cie.2020.106484>
- Ahmadi-Javid, A., Mansourfar, M., Lee, C.-G., & Liu, L. (2023). Optimal distribution of perishable foods with storage temperature control and quality requirements: An integrated vehicle routing problem. *Computers & Industrial Engineering*, 182, 109215. <https://doi.org/10.1016/j.cie.2023.109215>
- Ahumada, O., & Villalobos, J. R. (2009). Application of planning models in the agri-food supply chain: A review. *European Journal of Operational Research*, 196(1), 1–20. <https://doi.org/10.1016/j.ejor.2008.02.014>
- Alvarez, A., Cordeau, J.-F., Jans, R., Munari, P., & Morabito, R. (2020). Formulations, branch-and-cut and a hybrid heuristic algorithm for an inventory routing problem with perishable products. *European Journal of Operational Research*, 283(2), 511–529. <https://doi.org/10.1016/j.ejor.2019.11.015>
- Amorim, P., & Almada-Lobo, B. (2014). The impact of food perishability issues in the vehicle routing problem. *Computers & Industrial Engineering*, 67, 223–233. <https://doi.org/10.1016/j.cie.2013.11.006>
- Amorim, P., Günther, H.-O., & Almada-Lobo, B. (2012). Multi-objective integrated production and distribution planning of perishable products. *International Journal of Production Economics*, 138(1), 89–101. <https://doi.org/10.1016/j.ijpe.2012.03.005>
- Amorim, P., Meyr, H., Almeder, C., & Almada-Lobo, B. (2013). Managing perishability in production-distribution planning: A discussion and review. *Flexible Services and Manufacturing Journal*, 25(3), 389–413. <https://doi.org/10.1007/s10696-011-9122-3>
- Aouadni, S., Aouadni, I., & Rebaï, A. (2019). A systematic review on supplier selection and order allocation problems. *Journal of Industrial Engineering International*, 15(S1), 267–289. <https://doi.org/10.1007/s40092-019-00334-y>
- Arriaga-Lorenzo, P., De Jesús Maldonado-Simán, E., Ramírez-Valverde, R., Martínez-Hernández, P. A., Tirado-González, D. N., & Saavedra-Jiménez, L. A. (2023). Cold chain relevance in the food safety of perishable products. *Foods and Raw Materials*, 116–128. <https://doi.org/10.21603/2308-4057-2023-1-559>
- Aung, M. M., & Chang, Y. S. (2014). Traceability in a food supply chain: Safety and quality perspectives. *Food Control*, 39, 172–184. <https://doi.org/10.1016/j.foodcont.2013.11.007>
- Awad, M., Ndiaye, M., & Osman, A. (2020). Vehicle routing in cold food supply chain logistics: A literature review. *The International Journal of Logistics Management*, 32(2), 592–617. <https://doi.org/10.1108/IJLM-02-2020-0092>
- Banaeian, N., Mobli, H., Fahimnia, B., Nielsen, I. E., & Omid, M. (2018). Green supplier selection using fuzzy group decision making methods: A case study from the agri-food industry. *Computers & Operations Research*, 89, 337–347. <https://doi.org/10.1016/j.cor.2016.02.015>

- Bertazzi, L., Bosco, A., & Laganà, D. (2015). Managing stochastic demand in an Inventory Routing Problem with transportation procurement. *Omega*, 56, 112–121. <https://doi.org/10.1016/j.omega.2014.09.010>
- Boiteau, J. M., & Pingali, P. (2022). Food loss of perishable produce from farm to retail: Evidence from tomato supply chains in South India. *The American Journal of Clinical Nutrition*, 115(6), 1535–1548. <https://doi.org/10.1093/ajcn/nqac039>
- Can Atasagun, G., & Karaoğlu, İ. (2024). Solution approaches for the integrated production and outbound distribution scheduling problem with multiple plants and perishable items. *Expert Systems with Applications*, 237, 121318. <https://doi.org/10.1016/j.eswa.2023.121318>
- Chan, F. T. S., Wang, Z. X., Goswami, A., Singhania, A., & Tiwari, M. K. (2020). Multi-objective particle swarm optimisation based integrated production inventory routing planning for efficient perishable food logistics operations. *International Journal of Production Research*, 58(17), 5155–5174. <https://doi.org/10.1080/00207543.2019.1701209>
- Chen, H.-K., Hsueh, C.-F., & Chang, M.-S. (2009). Production scheduling and vehicle routing with time windows for perishable food products. *Computers & Operations Research*, 36(7), 2311–2319. <https://doi.org/10.1016/j.cor.2008.09.010>
- Chen, Z. (2018). Optimization of production inventory with pricing and promotion effort for a single-vendor multi-buyer system of perishable products. *International Journal of Production Economics*, 203, 333–349. <https://doi.org/10.1016/j.ijpe.2018.06.002>
- Coelho, L. C., Cordeau, J.-F., & Laporte, G. (2014). Heuristics for dynamic and stochastic inventory-routing. *Computers & Operations Research*, 52, 55–67. <https://doi.org/10.1016/j.cor.2014.07.001>
- Covert, R. P., & Philip, G. C. (1973). *An EOQ Model for Item with Weibull Distribution Deterioration*, *AIIE Transactions*, 5, (4), 323–326.
- Crivei, I. C., Marc, R. A., Rațu, R. N., Mureșan, C. C., Postolache, A. N., Stoica, F., Dumitru Veleşcu, I., & Albu, A. (2025). Advanced risk and hazard analysis in the egg sorting-packing units industry from supplier selection to delivery in chain stores under global food safety initiative integrated food safety programs. *Heliyon*, 11(4), e42587. <https://doi.org/10.1016/j.heliyon.2025.e42587>
- Dantzig, G. B., & Ramser, J. H. (1959). The Truck Dispatching Problem. *Management Science*, 6(1), 80–91.
- Devapriya, P., Ferrell, W., & Geismar, N. (2017). Integrated production and distribution scheduling with a perishable product. *European Journal of Operational Research*, 259(3), 906–916. <https://doi.org/10.1016/j.ejor.2016.09.019>
- Ekşioğlu, S. D., & Jin, M. (2006). Cross-Facility Production and Transportation Planning Problem with Perishable Inventory. In M. Gavrilova, O. Gervasi, V. Kumar, C. J. K. Tan, D. Taniar, A. Laganá, Y. Mun, & H. Choo (Eds.), *Computational Science and Its Applications—ICCSA 2006* (Vol. 3982, pp. 708–717). Springer Berlin Heidelberg. https://doi.org/10.1007/11751595_75
- Entrup, M. L., Grunow, M., Günther, H. O., Seiler, T., & van Beek, P. (2004). *SHELF LIFE INTEGRATED PLANNING IN YOGHURT PRODUCTION*.
- Ghare, & Schrader. (1963). *A Model for An Exponentially Decaying Inventory*, *The Journal of Industrial Engineering*, 14, (5), 238–243.
- Ghasemkhani, A., Tavakkoli-Moghaddam, R., Rahimi, Y., Shahnejat-Bushehri, S., & Tavakkoli-Moghaddam, H. (2022). Integrated production-inventory-routing problem for multi-perishable products under uncertainty by meta-heuristic algorithms. *International Journal of Production Research*, 60(9), 2766–2786. <https://doi.org/10.1080/00207543.2021.1902013>

- Gioia, D. G., Felizardo, L. K., & Brandimarte, P. (2023). Simulation-based inventory management of perishable products via linear discrete choice models. *Computers & Operations Research*, 157, 106270. <https://doi.org/10.1016/j.cor.2023.106270>
- Giri, B. C., & Chaudhuri, K. S. (1998). Deterministic models of perishable inventory with stock-dependent demand rate and nonlinear holding cost. *European Journal of Operational Research*, 105(3), 467–474. [https://doi.org/10.1016/S0377-2217\(97\)00086-6](https://doi.org/10.1016/S0377-2217(97)00086-6)
- Görçün, Ö. F., Aytekin, A., & Korucuk, S. (2023). Fresh food supplier selection for global retail chains via bipolar neutrosophic methodology. *Journal of Cleaner Production*, 419, 138156. <https://doi.org/10.1016/j.jclepro.2023.138156>
- Govindan, K., Jafarian, A., Khodaverdi, R., & Devika, K. (2014). Two-echelon multiple-vehicle location–routing problem with time windows for optimization of sustainable supply chain network of perishable food. *International Journal of Production Economics*, 152, 9–28. <https://doi.org/10.1016/j.ijpe.2013.12.028>
- Goyal, S. K., & Giri, B. C. (2001). Recent trends in modeling of deteriorating inventory. *European Journal of Operational Research*, 134(1), 1–16. [https://doi.org/10.1016/S0377-2217\(00\)00248-4](https://doi.org/10.1016/S0377-2217(00)00248-4)
- Goyal, S. K., & Giri, B. C. (2003). The production–inventory problem of a product with time varying demand, production and deterioration rates. *European Journal of Operational Research*, 147(3), 549–557. [https://doi.org/10.1016/S0377-2217\(02\)00296-5](https://doi.org/10.1016/S0377-2217(02)00296-5)
- Gulecyuz, S., O’Sullivan, B., & Armagan Tarim, S. (2025). A heuristic method for perishable inventory management under non-stationary demand. *Omega*, 133, 103267. <https://doi.org/10.1016/j.omega.2024.103267>
- Hajiaghaei-Keshteli, M., Cenk, Z., Erdebili, B., Selim Özdemir, Y., & Gholian-Jouybari, F. (2023). Pythagorean Fuzzy TOPSIS Method for Green Supplier Selection in the Food Industry. *Expert Systems with Applications*, 224, 120036. <https://doi.org/10.1016/j.eswa.2023.120036>
- Handayani, D. I., Kurnia Iswardani, Misra Hartati, Muhamad Zulkiflee Osman, & Mimik Umi Zuhroh. (2025). The Future of Supplier Selection: Integrating Bibliometric Intelligence and MCDM in The Perishable Agro-Industry. *Jurnal Manajemen Dan Agribisnis*, 22(2), 158. <https://doi.org/10.17358/jma.22.2.158>
- Hashemi-Amiri, O., Ghorbani, F., & Ji, R. (2023). Integrated supplier selection, scheduling, and routing problem for perishable product supply chain: A distributionally robust approach. *Computers & Industrial Engineering*, 175, 108845. <https://doi.org/10.1016/j.cie.2022.108845>
- He, Y., Huang, H., Li, D., Shi, V., & Wu, S. (2018). Quality and Operations Management in Food Supply Chains: A Literature Review. *Journal of Food Quality*, 2018, 1–14. <https://doi.org/10.1155/2018/7279491>
- Ho, W., Xu, X., & Dey, P. K. (2010). Multi-criteria decision making approaches for supplier evaluation and selection: A literature review. *European Journal of Operational Research*, 202(1), 16–24. <https://doi.org/10.1016/j.ejor.2009.05.009>
- Hosseini, S., Tajik, N., Ivanov, D., Sarder, M. D., Barker, K., & Khaled, A. A. (2019). Resilient supplier selection and optimal order allocation under disruption risks. *International Journal of Production Economics*, 213, 124–137. <https://doi.org/10.1016/j.ijpe.2019.03.018>
- Jacxsens, L., Devlieghere, F., & Debevere, J. (2002). Temperature dependence of shelf-life as affected by microbial proliferation and sensory quality of equilibrium modified atmosphere packaged fresh produce. *Postharvest Biology and Technology*, 26(1), 59–73. [https://doi.org/10.1016/S0925-5214\(02\)00004-2](https://doi.org/10.1016/S0925-5214(02)00004-2)

- Jedermann, R., Praeger, U., Geyer, M., & Lang, W. (2014). Remote quality monitoring in the banana chain. *Philosophical Transactions. Series A, Mathematical, Physical, and Engineering Sciences*, 372, 20130303. <https://doi.org/10.1098/rsta.2013.0303>
- Jedermann, R., Ruiz-Garcia, L., & Lang, W. (2009). Spatial temperature profiling by semi-passive RFID loggers for perishable food transportation. *Computers and Electronics in Agriculture*, 65(2), 145–154. <https://doi.org/10.1016/j.compag.2008.08.006>
- Ketzenberg, M. (2006). Information Sharing to Improve Retail Product Freshness of Perishables (ed.3). *Production and Operations Management*, 15. <https://doi.org/10.1111/j.1937-5956.2006.tb00003.x>
- Komijani, M., & Sheikh Sajadieh, M. (2024). An integrated planning approach for perishable goods with stochastic lifespan: Production, inventory, and routing. *Cleaner Logistics and Supply Chain*, 12, 100163. <https://doi.org/10.1016/j.clscn.2024.100163>
- Kumar, A., & Agrawal, S. (2023). Challenges and opportunities for agri-fresh food supply chain management in India. *Computers and Electronics in Agriculture*, 212, 108161. <https://doi.org/10.1016/j.compag.2023.108161>
- Kumar, A., Mangla, S. K., Kumar, P., & Song, M. (2021). Mitigate risks in perishable food supply chains: Learning from COVID-19. *Technological Forecasting and Social Change*, 166, 120643. <https://doi.org/10.1016/j.techfore.2021.120643>
- Lacomme, P., Moukrim, A., Quilliot, A., & Vinot, M. (2018). Supply chain optimisation with both production and transportation integration: Multiple vehicles for a single perishable product. *International Journal of Production Research*, 56(12), 4313–4336. <https://doi.org/10.1080/00207543.2018.1431416>
- Li, D., & Li, K. (2023). A multi-objective model for cold chain logistics considering customer satisfaction. *Alexandria Engineering Journal*, 67, 513–523. <https://doi.org/10.1016/j.aej.2022.12.067>
- Li, Y., Chu, F., Yang, Z., & Calvo, R. W. (2016). A Production Inventory Routing Planning for Perishable Food with Quality Consideration. *IFAC-PapersOnLine*, 49(3), 407–412. <https://doi.org/10.1016/j.ifacol.2016.07.068>
- Liu, L., & Liu, S. (2020). Integrated Production and Distribution Problem of Perishable Products with a Minimum Total Order Weighted Delivery Time. *Mathematics*, 8(2), 146. <https://doi.org/10.3390/math8020146>
- Marinelli, F., Nenni, M. E., & Sforza, A. (2007). Capacitated lot sizing and scheduling with parallel machines and shared buffers: A case study in a packaging company. *Annals of Operations Research*, 150(1), 177–192. <https://doi.org/10.1007/s10479-006-0157-x>
- Martin, M., & Iravo, A. (2014). Effect of Inventory Control Management on Mumias Sugar Retailers' Satisfaction Level: A Survey of Mumias Sugar Retailers in Kiambu County, Kenya. *International Journal of Academic Research in Business and Social Sciences*, 4(12), 83–100.
- Mohammed, A., Bai, C., Channouf, N., Ahmed, T. A., & Mohamed, S. M. (2023). G-resilient multi-tier supplier selection and order allocation in food industry: A hybrid methodology. *International Journal of Systems Science: Operations & Logistics*, 10(1), 2195055. <https://doi.org/10.1080/23302674.2023.2195055>
- Mohammed, A., Setchi, R., Filip, M., Harris, I., & Li, X. (2018). An integrated methodology for a sustainable two-stage supplier selection and order allocation problem. *Journal of Cleaner Production*, 192, 99–114. <https://doi.org/10.1016/j.jclepro.2018.04.131>
- Moosavi, J., Fathollahi-Fard, A. M., & Dulebenets, M. A. (2022). Supply chain disruption during the COVID-19 pandemic: Recognizing potential disruption management strategies. *International Journal of Disaster Risk Reduction*, 75, 102983. <https://doi.org/10.1016/j.ijdr.2022.102983>

- Mousavi, R., Bashiri, M., & Nikzad, E. (2022). Stochastic production routing problem for perishable products: Modeling and a solution algorithm. *Computers & Operations Research*, 142, 105725. <https://doi.org/10.1016/j.cor.2022.105725>
- Muriana, C. (2016). An EOQ model for perishable products with fixed shelf life under stochastic demand conditions. *European Journal of Operational Research*, 255(2), 388–396. <https://doi.org/10.1016/j.ejor.2016.04.036>
- Mustafa, M. F. M. S., Navaranjan, N., & Demirovic, A. (2024). Food cold chain logistics and management: A review of current development and emerging trends. *Journal of Agriculture and Food Research*, 18, 101343. <https://doi.org/10.1016/j.jafr.2024.101343>
- Nahmias, & Steven. (1982). *Perishable Inventory Theory: A Review*. 30, 680–708. <https://doi.org/10.1287/opre.30.4.680>
- Navazi, F., Sazvar, Z., & Tavakkoli-Moghaddam, R. (2021). A sustainable closed-loop location-routing-inventory problem for perishable products. *Scientia Iranica*, 0(0), 0–0. <https://doi.org/10.24200/sci.2021.55642.4353>
- Nikounam Nezami, M., Toloie Eshlaghy, A., & Iranban, S.-J. (2024). Modeling and simulation of supply chain resilience for unnecessary perishable foods using an agent-based modeling approach. *Journal of Industrial Engineering and Management Studies*, 11(1), 156–169. <https://doi.org/10.22116/jiems.2024.466113.1566>
- Orjuela Castro, J., & Jaimes, W. (2017). Dynamic impact of the structure of the supply chain of perishable foods on logistics performance and food security. *Journal of Industrial Engineering and Management*, 10, 687. <https://doi.org/10.3926/jiem.2147>
- Orjuela-Castro, J. A., Sanabria-Coronado, L. A., & Peralta-Lozano, A. M. (2017). Coupling facility location models in the supply chain of perishable fruits. *Research in Transportation Business & Management*, 24, 73–80. <https://doi.org/10.1016/j.rtbm.2017.08.002>
- Osvald, A., & Stirn, L. Z. (2008). A vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food. *Journal of Food Engineering*, 85(2), 285–295. <https://doi.org/10.1016/j.jfoodeng.2007.07.008>
- Padmanabhan, G., & Vrat, P. (1995). EOQ models for perishable items under stock dependent selling rate. *European Journal of Operational Research*, 86(2), 281–292. [https://doi.org/10.1016/0377-2217\(94\)00103-J](https://doi.org/10.1016/0377-2217(94)00103-J)
- Pan, L., Shan, M., & Li, L. (2023). Optimizing Perishable Product Supply Chain Network Using Hybrid Metaheuristic Algorithms. *Sustainability*, 15(13), 10711. <https://doi.org/10.3390/su151310711>
- Parfitt, J., Barthel, M., & Macnaughton, S. (2010). Food waste within food supply chains: Quantification and potential for change to 2050. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365(1554), 3065–3081. <https://doi.org/10.1098/rstb.2010.0126>
- Pol, S. M., Rayte, A., Patil, B. T., & Joshi, K. N. (2024). Analysis and Optimization of Transportation Logistics for Supply Chain Management of Perishable Goods using Monte Carlo Simulation. *E3S Web of Conferences*, 559, 04004. <https://doi.org/10.1051/e3sconf/202455904004>
- Pratap, S., Jauhar, S. K., Paul, S. K., & Zhou, F. (2022). Stochastic optimization approach for green routing and planning in perishable food production. *Journal of Cleaner Production*, 333, 130063. <https://doi.org/10.1016/j.jclepro.2021.130063>
- Qiu, Y., Qiao, J., & Pardalos, P. M. (2019). Optimal production, replenishment, delivery, routing and inventory management policies for products with perishable inventory. *Omega*, 82, 193–204. <https://doi.org/10.1016/j.omega.2018.01.006>
- Rafie-Majd, Z., Pasandideh, S. H. R., & Naderi, B. (2018). Modelling and solving the integrated inventory-location-routing problem in a multi-period and multi-perishable

- product supply chain with uncertainty: Lagrangian relaxation algorithm. *Computers & Chemical Engineering*, 109, 9–22. <https://doi.org/10.1016/j.compchemeng.2017.10.013>
- Rong, A., Akkerman, R., & Grunow, M. (2011). An optimization approach for managing fresh food quality throughout the supply chain. *International Journal of Production Economics*, 131(1), 421–429. <https://doi.org/10.1016/j.ijpe.2009.11.026>
- Sahoo, B., & Debnath, B. K. (2026). A spherical fuzzy decision-making approach for optimal supplier selection in the organic food retail sector. *Applied Soft Computing*, 187, 114202. <https://doi.org/10.1016/j.asoc.2025.114202>
- Sharma, J., Singh, S., Tyagi, M., & Powar, S. (2024). Avenues of decarbonisation in the dynamics of processed food supply chains: Towards responsible production consumption. *Heliyon*, 10(5), e26456. <https://doi.org/10.1016/j.heliyon.2024.e26456>
- Sharma, R., Kannan, D., Darbari, J. D., & Jha, P. C. (2024). Group decision making model for selection of performance indicators for sustainable supplier evaluation in agro-food supply chain. *International Journal of Production Economics*, 277, 109353. <https://doi.org/10.1016/j.ijpe.2024.109353>
- Shashi, S., Centobelli, P., Cerchione, R., & Ertz, M. (2021). Food cold chain management: What we know and what we deserve. *Supply Chain Management: An International Journal*, 26(1), 102–135. <https://doi.org/10.1108/SCM-12-2019-0452>
- Shi, H., Zhang, Q., & Qin, J. (2024). Cold Chain Logistics and Joint Distribution: A Review of Fresh Logistics Modes. *Systems*, 12(7), 264. <https://doi.org/10.3390/systems12070264>
- Shin, M., Lee, H., Ryu, K., Cho, Y., & Son, Y.-J. (2019). A two-phased perishable inventory model for production planning in a food industry. *Computers & Industrial Engineering*, 133, 175–185. <https://doi.org/10.1016/j.cie.2019.05.010>
- Soler, W. A. D. O., Santos, M. O., & Akartunalı, K. (2021). DECOMPOSITION BASED HEURISTICS FOR A LOT SIZING AND SCHEDULING PROBLEM ON MULTIPLE HETEROGENEOUS PRODUCTION LINES WITH PERISHABLE PRODUCTS. *Pesquisa Operacional*, 41(spe), e240377. <https://doi.org/10.1590/0101-7438.2021.041s1.00240377>
- Steinbacher, L. M., Rippel, D., Schulze, P., Rohde, A.-K., & Freitag, M. (2023). Quality-based scheduling for a flexible job shop. *Journal of Manufacturing Systems*, 70, 202–216. <https://doi.org/10.1016/j.jmsy.2023.07.005>
- Sun, H., Sun, S., Zhou, Y., & Xue, Y. (2023). Trade-offs between economic and environmental goals of production-inventory-routing problem for multiple perishable products. *Computers & Industrial Engineering*, 178, 109133. <https://doi.org/10.1016/j.cie.2023.109133>
- Tadei, R., Trubian, M., Avendaño, J. L., Della Croce, F., & Menga, G. (1995). Aggregate planning and scheduling in the food industry: A case study. *European Journal of Operational Research*, 87(3), 564–573. [https://doi.org/10.1016/0377-2217\(95\)00230-8](https://doi.org/10.1016/0377-2217(95)00230-8)
- Teng, J.-T., Ouyang, L.-Y., & Chen, L.-H. (2007). A comparison between two pricing and lot-sizing models with partial backlogging and deteriorated items. *International Journal of Production Economics*, 105(1), 190–203. <https://doi.org/10.1016/j.ijpe.2006.03.003>
- Theophilus, O., Dulebenets, M. A., Pasha, J., Lau, Y., Fathollahi-Fard, A. M., & Mazaheri, A. (2021). Truck scheduling optimization at a cold-chain cross-docking terminal with product perishability considerations. *Computers & Industrial Engineering*, 156, 107240. <https://doi.org/10.1016/j.cie.2021.107240>

- Tiwari, S., & Tiwari, K. (2024). *Enhancing Cold Chain Logistics for Perishable Foods: Integrating Advanced Technologies for Improved Quality, Safety, and Sustainability*. 2(7).
- Trienekens, J., & Zuurbier, P. (2008). Quality and safety standards in the food industry, developments and challenges. *International Journal of Production Economics, Research and Applications in E-Commerce and Third-Party Logistics Management*, 113(1), 107–122. <https://doi.org/10.1016/j.ijpe.2007.02.050>
- Vahdani, B., Niaki, S. T. A., & Aslanzade, S. (2017). Production-inventory-routing coordination with capacity and time window constraints for perishable products: Heuristic and meta-heuristic algorithms. *Journal of Cleaner Production*, 161, 598–618. <https://doi.org/10.1016/j.jclepro.2017.05.113>
- Valero, A., Carrasco, E., & Ma, R. (2012). Principles and Methodologies for the Determination of Shelf-Life in Foods. In A. Amer Eissa (Ed.), *Trends in Vital Food and Control Engineering*. InTech. <https://doi.org/10.5772/35353>
- Venkataraman, V., El-kharouf, A., Pandya, B., Amakiri, E., & Steinberger-Wilckens, R. (2020). Coupling of engine exhaust and fuel cell exhaust with vapour absorption refrigeration/air conditioning systems for transport applications: A Review. *Thermal Science and Engineering Progress*, 18, 100550. <https://doi.org/10.1016/j.tsep.2020.100550>
- Violi, A., De Maio, A., Fattoruso, G., & Olivieri, M. G. (2023). An age-based dynamic approach for distribution of perishable commodities with stochastic demands. *Soft Computing*, 27(11), 7039–7050. <https://doi.org/10.1007/s00500-023-07917-3>
- Violi, A., Laganá, D., & Paradiso, R. (2020). The inventory routing problem under uncertainty with perishable products: An application in the agri-food supply chain. *Soft Computing*, 24(18), 13725–13740. <https://doi.org/10.1007/s00500-019-04497-z>
- Wallace, C. A., Sperber, W. H., & Mortimore, S. E. (2018). *Food Safety for the 21st Century*.
- Wang, F., & Bo, H. (2025). Time-dependent integrated production and outbound distribution scheduling with multiple cold chain products considering carbon emissions. *International Journal of Production Economics*, 109836. <https://doi.org/10.1016/j.ijpe.2025.109836>
- Wang, G. (2021). Integrated supply chain scheduling of procurement, production, and distribution under spillover effects. *Computers & Operations Research*, 126, 105105. <https://doi.org/10.1016/j.cor.2020.105105>
- Wang, J., Wang, H., He, J., Li, L., Shen, M., Tan, X., Min, H., & Zheng, L. (2015). Wireless sensor network for real-time perishable food supply chain management. *Computers and Electronics in Agriculture*, 110, 196–207. <https://doi.org/10.1016/j.compag.2014.11.009>
- Wang, Y., Wang, W., Wang, Z., Deveci, M., Roy, S. K., & Kadry, S. (2024). Selection of sustainable food suppliers using the Pythagorean fuzzy CRITIC-MARCOS method. *Information Sciences*, 664, 120326. <https://doi.org/10.1016/j.ins.2024.120326>
- Wang, Y., Yi, J., Zhu, X., Luo, J., & Baiyang, J. (2015). Developing an Ontology-Based Cold Chain Logistics Monitoring and Decision System. *Journal of Sensors*, 2015, 1–8. <https://doi.org/10.1155/2015/231706>
- Xu, X., Guo, W. G., & Rodgers, M. D. (2020). A real-time decision support framework to mitigate degradation in perishable supply chains. *Computers & Industrial Engineering*, 150, 106905. <https://doi.org/10.1016/j.cie.2020.106905>
- Xue, N., Landa-Silva, D., Figueredo, G., & Triguero, I. (2019, February 19). *A Simulation-Based Optimisation Approach for Inventory Management of Highly Perishable Food*. <https://doi.org/10.5220/0007401304060413>

- Yantong Li, Feng Chu, Chengbin Chu, Wei Zhou, & Zhanguo Zhu. (2016). Integrated production inventory routing planning with time windows for perishable food. *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, 2651–2656. <https://doi.org/10.1109/ITSC.2016.7795982>
- Yazdekhashti, A., Wang, J., Zhang, L., & Ma, J. (2021). A multi-period multi-modal stochastic supply chain model under COVID pandemic: A poultry industry case study in Mississippi. *Transportation Research. Part E, Logistics and Transportation Review*, 154, 102463. <https://doi.org/10.1016/j.tre.2021.102463>
- Zhang, Y., Chai, Y., & Ma, L. (2021). Research on Multi-Echelon Inventory Optimization for Fresh Products in Supply Chains. *Sustainability*, 13, 6309. <https://doi.org/10.3390/su13116309>