

Simulation-Driven Decision Support Frameworks for Designing Resilient and Adaptive Bioenergy Supply Chain Networks

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ABSTRACT

Simulation-Driven Decision Support Frameworks for Designing Resilient and Adaptive Bioenergy Supply Chain Networks

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The increasing complexity and volatility of supply chains (SCs) underscores the importance of resilient and adaptive network design, particularly in the energy sector, where disruptions can compromise both security and continuity. Conventional static configurations are insufficient to handle several uncertainty sources and systemic interdependencies that can propagate failures across the network. As the global energy landscape transitions from fossil fuels to renewable sources, energy SCs must evolve into dynamically reconfigurable systems capable of continuous adaptation to market fluctuations and climate-induced disruptions.

Given the need to address these challenges and leverage opportunities offered by bioenergy production, this thesis develops simulation-driven frameworks for modeling adaptive and resilient biomass SC networks. The research begins with quantifying disruptions and their propagation across the network, where graph-theoretic analysis is combined with simulation to identify structural and operational vulnerabilities and measure cascading effects. In this setting, contingency plans are dynamically triggered, depending on the scale and nature of disruptions. This is followed by extending the digital modeling environment with an optimization layer that accounts for multiple sources of operational risks and supports adaptive replenishment planning under inventory policies across several nodes. In the third objective, the optimization layer is extended into a bi-level hierarchical model. At the upper level, multi-echelon production planning is optimized to align biomass supply availability with community energy demand under uncertainty. At the lower level, the model incorporates multi-modal transportation planning, taking into account heterogeneous fleet capacities. The two levels are connected through a coordinated network enabled by information-sharing mechanism. This thesis is applied to a case study of

remote off-grid communities in Quebec, where the objective is to integrate bioenergy, which is a locally available energy resource, into existing diesel-based energy networks under logistical constraints, including seasonal accessibility restricted to a limited navigable waterway.

By unifying disruption propagation analysis, resilience quantification, and adaptive risk-aware planning within a digital modeling paradigm, this thesis advances the development of next-generation SC networks that are structurally robust and operationally agile in the face of multidimensional uncertainty. Moreover, the research brings together ideas from simulation modeling, derivative-free optimization, and natural resource management, which can foster the development of resilient, sustainable, and affordable energy sources while promoting equity within communities.

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To my mother, my sister, and all women of Iran

*the eternal flame of resilience,
the unbroken voice of freedom,
and the light that continues to rise, even beyond shadows.*

This work is but a small tribute to your courage and dreams.

Contribution of Authors

This thesis has been prepared in a *manuscript-based* format under the supervision of Dr. Fereshteh Mafakheri and Dr. Chun Wang. All articles included in this thesis were co-authored and reviewed by Dr. Mafakheri and Dr. Wang prior to their submission for publication. The candidate served as the principal researcher, undertaking the development of mathematical models, programming of solution algorithms, analysis and validation of results, as well as the preparation of the manuscripts. All co-authors reviewed and approved the final versions of the articles.

Journal Publications

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List of Abbreviations

BSC	Biomass Supply Chain
SC	Supply Chain
SCR	Supply Chain Resilience
SCM	Supply Chain Management
SCN	Supply Chain Network
DSF	Decision Support Framework
IEA	International Energy Agency
ABS	Gent-Based Simulation
DES	Discrete Event Simulation
DFO	Derivative-Free Optimization
SD	System Dynamics
SDGs	United Nations Sustainable Development Goals
CO ₂	Carbon Dioxide
KPI	Key Performance Indicators
MCDM	Multi-Criteria Decision-Making
LP	Linear Programming
DEA	Data Envelopment Analysis
DEMATEL	Decision-Making Trial and Evaluation Laboratory
ANP	Analytic Network Process
BWM	Best Worst Method
TOPSIS	Technique For Order of Preference by Similarity to Ideal Solution
MIP	Mixed-Integer Programming
MILP	Mixed Integer Linear Programming
2SSP	Two-Stage Stochastic Programming
MSSP	Multi-Stage Stochastic Programming
FP	Fuzzy Programming
RP	Robust Programming
TEA	Techni-Economic Analysis

LCA	Life Cycle Assessment
GIS	Geographic Information Systems
ML	Machine Learning
GHG	Greenhouse Gas

Chapter 1: Introduction

1.1. Background and Motivation

Today, the world is in the middle of a global energy crisis triggered by geopolitical tensions that have resulted in a substantial surge in fossil fuel prices. Simultaneously, the record concentration of carbon dioxide (CO₂) in the atmosphere is at its highest level in the past 650,000 years, representing a troubling increase in health risks and environmental degradation associated with climate change (IEA, 2022a). All these problems have intensified the global pursuit of cleaner, more sustainable, and resilient energy alternatives capable of ensuring both energy security and affordability (Bhatt et al., 2025). Among the diverse portfolio of renewable energy sources, biomass has emerged as the primary contributor to the global renewable energy mix, which represents nearly 55% of total renewable energy utilization worldwide (IEA, 2022b). The widespread availability of feedstock, ranging from forestry residues and agricultural byproducts to municipal solid waste, enhances the economic competitiveness and accessibility of biomass across regions. In addition to its environmental benefits, the global biomass market has demonstrated strong economic potential, valued at USD 127.4 billion in 2022 and expected to reach USD 203.2 billion by 2032, with an annual growth rate of 4.8% (Kawa and Dujak, 2025).

Biomass is not only a renewable and carbon-neutral energy source but also a versatile resource capable of generating electricity, heat, and biofuels. Moreover, its utilization extends beyond energy applications to the production of high value bioproducts, such as particleboard, fiberboard, biocomposites, and chemical feedstocks for the construction, furniture, food, and pharmaceutical industries (Kawa and Pierański, 2023). Such multi-functionality underscores biomass's potential to contribute to both energy transition and bioeconomic development, facilitating a more circular and resource-efficient economy. Between 2009 and 2019, the share of renewable energy in total final energy consumption rose notably across key sectors, from 19.4% to 26.0% in power generation, 10.7% to 14.7% in buildings, 12.5% to 16.1% in industry and agriculture, and 2.4% to 3.6% in transportation. This upward trend reflects a growing transition toward renewable energy in specific applications, with an increasing number of countries leveraging its environmental and economic advantages (Ransikarbum and Pitakaso, 2024). In the Canadian context, biomass represents a strategically significant resource for advancing national

decarbonization objectives. Forests cover approximately 35% of Canada's total land area, equivalent to about 10% of the world's forested land (Statistics Canada, 2018). This vast renewable resource base positions Canada as a global leader in sustainable forest management and biomass utilization. Through the efficient mobilization and conversion of these bioresources, Canada can accelerate its progress toward net-zero greenhouse gas (GHG) emissions, enhance energy resilience, and reduce reliance on imported fossil fuels, particularly in remote and off-grid communities (Statistics Canada, 2024).

The United Nations Sustainable Development Goals (SDGs), established in 2015, provide a universal framework of 17 interconnected goals designed as a “shared blueprint for peace and prosperity for people and the planet, now and into the future” to be achieved by 2030 (United Nations, 2017). While broad in scope, the SDGs have driven significant interdisciplinary research focused on embedding sustainability at the core of technological, economic, and social systems. The sustainable development of bioenergy, particularly biomass, directly supports multiple SDGs, including Goal 7 (Affordable and Clean Energy), Goal 12 (Responsible Consumption and Production), and Goal 13 (Climate Action), by enabling renewable energy deployment, promoting resource efficiency, and reducing GHG emissions (Piedra-Jimenez et al., 2024). Beyond energy provision, biomass fosters circular economy practices, supports rural development, and enhances energy equity, making it a strategic tool for achieving environmental and socio-economic objectives (Jazinaninejad et al., 2022). Consequently, the global emphasis on sustainability has intensified research in engineering, environmental science, and process systems engineering to optimize bioenergy production and conversion technologies to ensure that bioenergy contributes decisively to the transition toward a low-carbon and resilient energy future.

1.2. Problem Statement

Despite its significant potential and multiple benefits, the utilization of biomass for renewable energy production is not without challenges, primarily due to the inherent complexity, variability, and vulnerability of biomass supply chains (BSCs). Biomass feedstock is geographically dispersed and subject to seasonal availability, weather variability, and fluctuating chemical and physical properties (Jazinaninejad et al., 2022). These factors create uncertainties in feedstock supply and energy production, necessitating large-scale storage and customized processing strategies (Valipour et al., 2024). Logistical challenges further amplify the vulnerability of BSCs. Long

transportation distances, infrastructure constraints, and extreme weather can disrupt biomass delivery, while the diversity of feedstock types and conversion technologies increases coordination complexity across the network (Bhatt et al., 2025). Additionally, biomass conversion processes involve technologically complex operations, which are susceptible to equipment failures and operational disruptions, and consequently affect overall SC performance. The combination of feedstock variability, preprocessing requirements, complex logistics, and technological uncertainties makes BSCs inherently dynamic and more prone to disruptions compared to other conventional supply chains (SCs). Consequently, there is a critical need for resilient, adaptive, and optimized BSC design that can efficiently manage uncertainties, integrate preprocessing and conversion facilities, and ensure reliable, cost-effective, and sustainable energy production (Ebrahimi et al., 2025). Addressing these challenges is essential to fully realize the potential of biomass in supporting the global energy transition, achieving climate targets, and advancing circular economy objectives. Given the need to overcome such shortcomings while leveraging opportunities within BSCs, this thesis aims to design a real-time and resilient BSC and optimize its operations under uncertainties and disruptions.

1.3. Objectives and Purposes

This thesis aims to investigate the operational decision-making of BSCs under stochastic and uncertain conditions. The research begins with a systematic review of existing studies to identify critical logistical challenges and research gaps. Emphasizing the strategic role of intermediary nodes, particularly bio-hubs, in enhancing system adaptability and efficiency, three decision-support frameworks (DSFs) are subsequently developed to model the dynamic behavior of BSCs and optimize their operational planning under uncertainty and disruption. In the first DSF, a digital simulation-driven framework is developed for modeling adaptive and resilient SC networks in the face of uncertainty, where the focus is on modeling disruptions and their propagation across the network. In this setting, contingency plans are dynamically triggered. This is followed by extending the digital modeling environment with an optimization layer that incorporates multiple sources of operational risks and supports coordinating tactical and operational planning across several nodes. This thesis shows how advanced optimization algorithms, integrated with simulation, can generate plans for both mitigation measures and tactical responses. By unifying disruption propagation analysis, resilience quantification, and adaptive risk-aware planning within

a digital modeling paradigm, this research advances the development of next-generation SC networks that are structurally robust and operationally agile in the face of potential disruptions. To achieve the above objectives, the main research contributions along with the main DSFs are summarized as follows:

1.3.1. Analyzing Key Enablers of BSCs

This thesis first identifies the key enablers facilitating the large-scale mobilization of bioresources through a systematic literature review, with a particular focus on the integration of bio-hubs. The findings have highlighted the critical role of bio-hubs in enhancing the overall resilience, sustainability, and cost-effectiveness of BSCs by improving feedstock aggregation, preprocessing efficiency, and logistical coordination (Valipour et al., 2024). Despite their strategic importance, bio-hubs remain insufficiently explored in academic literature. By analyzing studies from the past decade, this research has addressed existing knowledge gaps and underscored the need for more integrated modeling approaches that link strategic design with operational decision-making.

1.3.2. Developing Resilience Measurement Framework to Capture Disruption Propagation Under Recovery Strategies

Since network configuration significantly affects its capacity to prepare, respond, and recover from disruption, it is crucial to redesign and test different network topologies under various disruption scenarios. To this end, a multi-agent simulation model was developed within a geographic information system environment to model the interactions and behaviours of autonomous agents within the SC network. Following this, several mitigation strategies, such as backup suppliers and backup inventory, were integrated into the model design to enhance resilience. These strategies were paired with disruption scenario settings, including inputs like the number of nodes or links disrupted, the intensity of each disruption, and the duration of these disruptions for each affected node in the network. To reflect the unpredictable nature of disruptions in real-world scenarios, a dynamic disruption threshold was proposed for activating resilience strategies instead of considering predetermined static time periods. After simulating scenarios over a defined planning horizon, the observed outcomes were used to characterize the overall network resilience through the resilience measurement indicators. To achieve this, six distinct indicators of reliability, preparedness, responsiveness, persistence, resourcefulness, and recovery time were utilized. These indicators were quantified using three structural metrics derived from the key network

characteristics of density, criticality, and connectivity. Each of these indicators was measured during pre-disaster, disaster, and post-disaster periods to capture the ripple effect of the disruptions and illustrate the behavior of the redesigned network.

1.3.3. Developing a Simulation-Based Optimization DSF for Replenishment Planning under Inventory Policies

This framework aims to enhance the resilience and operational continuity of BSCs by integrating adaptive inventory control with a dynamic dual sourcing mechanism. The model primarily supports bioenergy utilization while allowing temporary switching to diesel during periods of feedstock shortage, transportation disruption, or processing delays. It accounts for multiple sources of uncertainty, including fluctuations in feedstock quality, stochastic process times, variable transportation conditions, and limited storage capacities across facilities. Incorporating these stochastic dynamics increases system complexity and expands the decision space, which makes traditional optimization models infeasible. To address this, a simulation-based optimization approach is employed, coupling an agent-based simulation (ABS) model with an optimization layer to iteratively evaluate and refine inventory and sourcing decisions. This integration enables the derivation of robust, cost-efficient, and low-emission operational strategies that maintain system functionality under uncertainty and ensure a reliable energy supply to end users.

1.3.4. Developing a Bi-Level Optimization Approach for Coordinating Logistics Planning

This study formulates a coordinated decision-making framework to manage a fully biomass-dependent energy system, where diesel substitution is not permitted. In such a context, the continuous and reliable flow of biomass resources becomes vital to sustain bioenergy generation. To address this dependency, the framework incorporates a scenario-based supplier disruption model to capture uncertainties associated with biomass availability, along with transportation interruptions that can propagate across the supply network. A bi-level derivative-free optimization structure is designed to integrate strategic and operational decisions within a multi-echelon BSC. The upper-level model determines replenishment and capacity allocation policies under uncertain supply and processing conditions, while the lower-level model focuses on optimizing transportation planning, considering multimodal routing, heterogeneous fleet configurations, and seasonal accessibility constraints. A coordination mechanism facilitates iterative information

exchange between the two levels, ensuring dynamic alignment between procurement, bio-hub processing, and logistics execution. The decision environment is further enhanced through agent-based simulation, which captures stochastic behaviors, inter-tier feedback effects, and cascading disruptions within the network. Through this integration, the framework supports synchronized decision-making and robust operational performance, maintaining supply continuity, optimizing resource utilization, and enhancing the resilience of bioenergy systems under uncertainty.

1.4. Thesis Structure

The thesis is structured to provide a systematic progression from conceptual foundations to methodological development and applied analysis. It begins with a comprehensive literature review in Chapter 2 that establishes the theoretical and empirical foundations of BSCs. This chapter examines existing research on SC resilience, BSC logistics, and bioenergy system modeling to identify key challenges, emerging trends, and research gaps that motivate the subsequent methodological developments. Chapter 3 examines the key enablers of BSCs, with a particular focus on the integration of bio-hubs within BSC networks. This chapter evaluates their ability to improve feedstock aggregation, preprocessing efficiency, and system adaptability while identifying the operational and structural challenges that limit large-scale biomass mobilization. Building on these insights, Chapter 4 develops a resilience measurement framework based on the triple resilience capacities (i.e., absorptive, adaptive, and restorative). The proposed framework models disruption propagation and recovery dynamics, offering a comprehensive approach to quantify the robustness and adaptive performance of bioenergy networks. Chapter 5 introduces a simulation-based optimization framework that integrates stochastic inventory management with dynamic dual sourcing mechanisms. This approach ensures reliable replenishment planning under uncertainty while enhancing operational continuity and efficiency. The study then advances a bi-level optimization framework in Chapter 6 to coordinate logistics planning within a fully biomass-dependent energy system. It incorporates supplier disruption modeling, multimodal transportation constraints, and iterative coordination between operational decision layers to maintain uninterrupted biomass flow. Finally, Chapter 7 synthesizes the findings, highlights theoretical and practical contributions to resilient SC design, and outlines directions for future research.

Chapter 2: Literature Review

This chapter establishes the theoretical and conceptual foundations that shape the whole dissertation. While each chapter is associated with a dedicated literature review pertinent to its methodological scope, this section consolidates the underlying principles that frame the study as a cohesive body of work. The dissertation is founded on the analysis and design of multi-echelon biomass supply chains (BSCs) that facilitate the transition from fossil-based to renewable energy pathways within the circular bioeconomy. The chapter draws upon theories of supply chain resilience (SCR) and systems thinking to conceptualize bioenergy networks as complex adaptive systems characterized by stochastic behavior, interdependent processes, and multi-level decision structures. Within this context, the thesis explores how the spatial and operational integration of intermediary nodes (i.e., bio-hubs) enhances coordination, efficiency, and reliability across the biomass value chain. Particular emphasis is placed on the development of operational planning and coordination mechanisms that account for uncertainty, seasonal accessibility, and resource variability. The theoretical discussion extends to resilience and adaptive operational planning, highlighting how disruptions propagate through interconnected logistics networks and how these can be mitigated through robust inventory control, flexible fleet management, and dynamic decision support frameworks (DSFs).

2.1. Resilience Quantification of Biomass Supply chains

2.1.1. Supply Chain Resilience Theory

Risks within Supply Chains (SCs) are varied and can be categorized as operational risks and disruption risks (Xu et al., 2020). Operational risks pertain to disruptions occurring in day-to-day SC operations, such as fluctuations in lead times and demand. On the other hand, disruption risks involve infrequent yet impactful events, including man-made disasters, natural calamities, and pandemics. These risks have a profound effect on the structure of the supply chain network (SCN) as certain suppliers, factories, distribution centers, and transportation routes become temporarily inaccessible (Hosseini et al., 2019). Consequently, material scarcities and delivery delays propagate downstream echelons and affect the SC's performance (Ivanov, 2020). Due to the increasing structural complexity, as well as frequency and intensity of various unpredictable events in today's dynamic environment, SCs are becoming more vulnerable to disruptions. Therefore,

enhancing the SCR is the key to mitigating potential risks and ensuring continuity in operation (Drozdbob et al., 2023). Although there are different definitions for SCR in the literature, the most comprehensive one describes it as the capability of the SCN to be prepared for potential disruptions, mitigate their impact when they do occur, and shorten the time needed to return to the normal state (Habibi et al., 2023b).

There are two broad types of resilience strategies to tackle these disruptions, i.e., proactive (absorptive) and reactive (adaptive or restorative) strategies (Faruquee et al., 2024). Proactive practices are adopted irrespective of disruptions, whereas reactive tactics are activated in response to disruptions to restore the SC to its initial condition. (Liu et al., 2023). Existing studies primarily concentrate on proactive strategies demonstrating their effectiveness in addressing various types of disruptions. Specifically, Olivares-Aguila and ElMaraghy (2021) demonstrated that taking post-disruption actions is not advantageous in the long-term performance improvement of the SC. However, the main question is how the impact of such strategies can be quantitatively assessed, given the multifaceted nature of resilience.

The concept of resilience capacity was introduced by Biringer et al. (2013), which includes absorptive, adaptive, and restorative capacities. Each capacity represents the temporal behavior of a network prior to (i.e., pre-disaster), during (i.e., at-disaster), and following a disruption occurrence (i.e., post-disaster). These capacities are considered as three lines of defence to harness disruptions and keep an acceptable performance level. The better performance of the initial lines can decrease the effort required in the subsequent lines (Hosseini et al., 2019). As such, resilience assessment indicators should evaluate these capacities simultaneously to provide comprehensive insights into the network's ability and the effectiveness of adopted resilience strategies in managing disruptions.

In the context of BSCs, the quantification of resilience and the design of effective recovery strategies are particularly critical due to the sector's inherent operational and structural vulnerabilities. BSCs face unique challenges such as seasonal variability in feedstock availability, weather-dependent accessibility, storage limitations, and geographically dispersed facilities (Valipour et al., 2025). Disruptions in these networks, whether due to transportation delays, extreme weather events, or processing facility outages, can quickly propagate across the network and lead to material shortages, energy supply interruptions, and increased operational costs (Habibi et al., 2023b). Consequently, measuring the resilience of BSCs is essential for identifying

bottlenecks, evaluating the effectiveness of proactive and reactive strategies, and informing decision-making under uncertainty. Quantitative resilience assessment, through indicators that capture absorptive, adaptive, and restorative capacities, allows managers to determine not only the system's ability to withstand disruptions but also the efficiency and speed with which it can recover. As such, decision-makers can prioritize investments in buffer capacities, flexible routing, inventory management, and contingency protocols to ensure continuity of bioenergy supply, enhancing system robustness, and reducing the socio-economic and environmental risks associated with energy shortages (Gital and Bilgen, 2024b).

2.1.2. Literature on Resilience Measurement

In order to identify the main contributions of this work to literature in this context, an analysis is conducted on papers that have addressed two key aspects simultaneously: evaluating SCR and quantitatively measuring the impact of resilience and/or resilience strategies. Table 2.1 provides an overview of studies closely related to this concept. As shown, a variety of quantitative methods and measurements have been adopted by these studies to analyze resilience. Several studies leveraged multi-criteria decision-making (MCDM) techniques such as DEMATEL, TOPSIS, BWM and ANP to identify and assess resilience drivers (Salehi et al., 2022; Ayyildiz, 2023; Vergara et al., 2023). Within this category, authors have tried to provide a set of indicators based on the resilience drivers and sustainability factors and analyze their effects on network resilience. However, accurately measuring some proposed attributes, such as operational readiness, SC visibility, and continuity management presents significant challenges in the real world. Another widely used method in the literature is optimization models, such as stochastic, robust, and fuzzy models (Behzadi et al., 2020; Izadikhah et al., 2021; Khezerlou et al., 2021; Ribeiro and Barbosa-Póvoa, 2023; Mirzaee et al., 2024; Jabbarzadeh and Shamsi, 2025), where specific metrics have been introduced to evaluate the resilience of objective functions. Common metrics in this category include cost, recovery level, lead time, and unmet demand. However, these measures alone may not fully capture the overall resilience of a SCN. For instance, equal recovery times do not necessarily indicate the same level of resilience, as networks may vary significantly in their structural configurations and interconnections (Habibi et al., 2023b).

Table 2.1. Summary of the literature review on SCR modeling

Author(s)	Modeling approach	Resilience strategy	Resilience metric	Resilience capacity			Interdependence among entities	Disruption	Recovery threshold	Ripple Effect	Operational risk	Case Study
				Absorptive	Adaptive	Restorative						
Fang and Zio (2019)	Robust optimization	✓	Lost performance during recovery		✓	✓						Power and gas
Li et al. (2020)			Robustness and Recoverability		✓	✓				✓		Automotive industry
Dixit et al (2020)	Monte Carlo Simulation		Network density, centrality, size, and connectivity		✓	✓						-
Hosseini et al. (2020)	Markov chain and Bayesian network		Expected utility and service level		✓	✓				✓		RFID blocking bi-fold wallet
Behzadi et al. (2020)	Stochastic optimization	✓	Net present value of the profit loss			✓						Agricultural
Olivares-Aguila and ElMaraghy (2021)	SD		Service level, cost, profit, and inventory on hand		✓	✓						-
Moosavi and Hosseini (2021)	DES (Anylogistix)	✓	Resilience loss			✓	✓					LED panel light
Taghizadeh et al. (2021)	DES		Lost demand		✓	✓	✓					Automotive
Izadikhah et al. (2021)	Two-stage DEA model and fuzzy chance constraints		Delay time		✓							Public transport system
Shi and Mena (2021)	Bayesian Network		Operational indicators	✓		✓						Automotive
Khezerlou et al. (2021)	Risk-averse optimization	✓	Financial metrics			✓					✓	BSC
Ni et al. (2022)	Monte Carlo Simulation		Resilience rate and satisfaction rate			✓						Oil SC
Kazemian et al. (2022)	DEMATEL and ANP		Structural metrics		✓							Automotive
Agarwal et al. (2022)	Graph theory		Based on SCR drivers		✓							Automobile
Ekinici et al. (2022)	SD		Entropy measurement	✓		✓						Global SCs
Hosseini and Ivanov (2022)	Bayesian network		Based on vulnerability and recoverability of supplier	✓		✓				✓		Automotive

Table 2.1 (Continued)

Author(s)	Modeling approach	Resilience strategy	Resilience metric	Resilience capacity								Case Study
				Absorptive	Adaptive	Restorative	Interdependence among entities	Disruption	Recovery threshold	Ripple Effect	Operational risk	
Rajesh (2022)	Incidence analysis and grey theory		Based on SCR drivers		✓							Electronic
Yazdanparast et al. (2022)	Scenario based-stochastic	✓	Financial metrics			✓						BSC
Salehi et al. (2022)	TOPSIS, and robust optimization	✓	Based on SCR drivers		✓						✓	BSC
Piya et al. (2022)	Interpretive structural modelling and DEMATEL		Based on SCR drivers		✓							Oil and gas
Ribeiro and Barbosa-Póvoa (2023)	Deterministic optimization model		Customer service level			✓				✓		A general SC
Xu et al. (2023)	Fuzzy double-feedback adjustment control system		Affordability and recovery level	✓		✓						
Ayyildiz (2023)	BWM and IVIF-AHP		Based on SCR drivers		✓							
Vergara et al. (2023)	DEMATEL and ANP		Based on SCR drivers		✓							Automotive
Gital and Bilgen (2024b)	Scenario-based optimization	✓	Financial and operational metrics			✓						BSC
Marcucci et al. (2024)	Fuzzy cognitive map		Based on SCR drivers		✓					✓		Agri-food SC
Mirzaee et al. (2024)	Stochastic optimization	✓	Financial metrics			✓				✓		A green SC
Jabbarzadeh and Shamsi (2025)	DEA, artificial neural network, and robust optimization		Financial metrics			✓					✓	Bioethanol supply chain
This study	ABS	✓	Structural, operational, and financial metrics	✓	✓	✓	✓	✓	✓	✓	✓	BSC

DEA: Data envelopment analysis, **DEMATEL:** Decision-making trial and evaluation laboratory, **ANP:** Analytic network process, **BWM:** Best worst method, **IVIF:** Interval valued intuitionistic fuzzy analytic, **AHP:** Analytic hierarchy process, **TOPSIS:** Technique for order of preference by similarity to ideal solution

Different simulation methods have been also adopted in the literature pool to quantify SCR. System dynamics (SD) was adopted by several studies (Olivares-Aguila and ElMaraghy, 2021; Ekinici et al., 2022) to analyze SC behavior and assess the impacts of disruptions on overall performance. In these studies, resilience metrics such as service level, financial metrics, and inventory level have been proposed, which are often overly narrow in focus. For example, if two distinct SCNs achieve comparable service levels, it cannot be assumed that their resilience is equivalent. Using discrete event simulation (DES), Moosavi and Hosseini (2021) quantified resilience loss by measuring the number of goods not received by recipients. However, this metric may not provide a complete picture of resilience. For instance, if a disruption occurs due to a sudden equipment failure that does not impact service levels, the measurement cannot capture this event as a loss of resilience (Habibi et al., 2023b). A similar limitation exists in the study by Taghizadeh et al. (2021), which assessed SCR solely based on lost demand. In the other study, Ni et al. (2022) utilized Monte Carlo simulation to evaluate resilience, incorporating resilience and satisfaction rates.

While the majority of studies have concentrated on measuring SCR, only a limited number have explored recovery-based approaches. Fang and Zio (2019) measured lost performance during recovery under facility fortification and backup facility strategies. Behzadi et al. (2020) presented an indicator based on the net present value of the profit loss to quantify the impact of having backup capacity in the system. Moosavi and Hosseini (2021) adopted the resilience loss indicator proposed by Torabi et al. (2015) to compare the performance of proposing backup supplier and backup inventory plans under supplier disruption. Khezerlou et al. (2021) investigated the impact of incorporating backup facilities and reinforced connection links to mitigate the effects of facility disruptions. They measured resilience based on the total cost of their network. Yazdanparast et al. (2022) developed a stochastic model to evaluate the impact of supply and production disruptions. Their approach incorporated resilience strategies such as prepositioning emergency inventory, flexible supply contracts, alternative production routes, and infrastructure fortification, with the cost profile serving as the primary metric for resilience assessment. Mirzaee et al. (2024) calculated financial metrics associated with incorporating backup suppliers, multiple sourcing, temporary facilities, blockchain, safety stock, and stockpiling strategies. Gital and Bilgen (2024) employed the financial (e.g., cost) and operational metrics (e.g., production level) to quantify the impact of adopting multi-sourcing, coverage distance, and backup assignment practices.

2.2. Operational Planning of Biomass Supply Chains

2.2.1. Inventory Management

In the SC management context, inventory control emerges as an important factor in improving operational efficiency and responsiveness (Kaynov et al., 2024). By ensuring that the right amount of stock is available at the right time, inventory management helps minimize stockouts, excess inventory, and consequently total cost while maintaining a balance between supply and demand (Ivanov et al., 2021). In dynamic and competitive SCs, this balance is crucial as it directly affects an organization's ability to meet customer expectations and maintain smooth production processes (Esrar et al., 2023). The increasing emphasis on sustainability has broadened the scope of inventory management beyond cost and service level objectives. Modern SC strategies increasingly incorporate environmental considerations, such as reducing carbon emissions and waste generated by overproduction or excess inventory (Pilati et al., 2024). In addition to operational and sustainability considerations, inventory plays a central role in SC resilience by acting as a strategic buffer that enables firms to absorb shocks and maintain service continuity during disruptions (e.g., supplier unreliability, geopolitical conflicts, pandemics, or climate-related events) (Maharjan and Kato, 2022). Rather than functioning solely as an operational tool, inventory serves as a risk-mitigation strategy. From a planning perspective, it provides flexibility to smooth variability across different echelons of SCs, which is an important function in long lead time or seasonal contexts where replenishment is constrained (Gital and Bilgen, 2024). Strategically positioned at key nodes, inventory enhances resilience by supporting robustness, adaptability, and recoverability, which in turn help firms absorb disruptions and recover more quickly (Hosseini et al., 2019). Complementing other resilience strategies, including redundancy, supply diversification, and flexible transportation, inventory offers an immediate cushion against unforeseen events. When embedded within broader SC frameworks, it becomes a proactive mechanism that balances cost efficiency with preparedness to ensure both economic viability and resilience in increasingly volatile environments (Kroes et al., 2025).

In the context of BSCs, effective inventory planning becomes even more critical due to the unique challenges of seasonality, quality degradation, and storage limitations (Habibi et al., 2023a). Unlike conventional SCs with relatively predictable replenishment, biomass systems face fluctuating availability, long lead times, and strong dependence on climatic conditions (Esmaeili et al., 2023). Strategic planning of inventory levels and replenishment schedules can mitigate the risk of energy shortages to ensure a reliable bioenergy supply and reduce reliance on backup energy sources during disruptions (Nair et al., 2024). Thus, inventory planning in

BSCs not only enhances cost-effectiveness and sustainability but also strengthens resilience and enables communities to maintain energy security under uncertainty.

2.2.2. Logistics Planning

In today's highly interconnected and volatile global economy, logistics planning has emerged as a fundamental element of SC management, directly influencing operational efficiency, resilience, and sustainability (Ebrahimi et al., 2025). Logistics activities are deeply interdependent rather than isolated, so that a single misstep at one node can cascade throughout the network. Such disruptions can affect upstream and downstream flows, increase costs, create bottlenecks, reduce asset utilization, and ultimately undermine service continuity and overall SCR (Aldrighetti et al., 2021; Habibi et al., 2023b). Within this broader landscape, BSCs represent a particularly challenging and strategically significant application domain, where the role of logistics planning becomes even more critical. The inherent complexity of BSCs and high variability in biomass characteristics not only introduce uncertainty in the available resources but also make logistics planning a central determinant of system performance (Habibi et al., 2023a). Efficient planning in BSCs is essential for mobilizing, preprocessing, and transporting biomass in a timely, cost-effective, and reliable manner (Valipour et al., 2024). Unlike conventional SCs, biomass flows are highly seasonal, weather-dependent, and subject to limited accessibility, particularly in remote regions, which amplifies the operational challenges (Mafakheri et al., 2021). Poorly planned logistics can lead to underutilized fleets, excessive inventory holding, delivery delays, and bottlenecks at different echelons and tiers, and consequently impact the continuity of energy supply and overall system efficiency (Ebrahimi et al., 2025). Moreover, the share of logistics costs (e.g., wood pellet) in biomass operations, can range from 34 % to 77 % of the total SC costs (WBA, 2018), which underscores the financial and strategic importance of careful planning. Within this context, coordination mechanisms play a critical role in ensuring that logistics decisions (e.g., fleet deployment, routing, scheduling, inventory management, and storage allocation) are systematically aligned across SC entities (Gital and Bilgen, 2024a). By facilitating real-time information exchange, harmonizing resource allocation, and enabling adaptive responses to seasonal and weather-induced disruptions, such mechanisms enhance the resilience, efficiency, and reliability of biomass supply networks (Jazinaninejad et al., 2022; Habibi et al., 2023a).

2.2.3. Related Works

SCs represent complex, multi-tiered networks that govern the flow of materials, information, and value from raw material suppliers to final consumers (Richey et al., 2022). Within this broader structure, logistics functions provide the operational backbone by managing the planning, execution, and coordination of goods movement and storage, extending beyond the scope of transportation management alone. In the context of BSCs, recognizing this distinction is crucial, as logistics and SC decisions are inherently interdependent and should be jointly optimized to enhance efficiency, resilience, and long-term sustainability (Nugroho and Zhu, 2024). Storage and transportation constitute two foundational components of logistics management. Accordingly, the majority of prior research has incorporated tactical and operational storage planning, alongside diverse aspects of transportation planning (e.g., shipment size and fleet size). Typically, these decisions are made together with strategic decisions and rely on a set of balance constraints that determine the quantities to ship and store, while optimizing the objective function. To better understand these dynamics and contribution of this research, studies in the context of BSCs which have explicitly incorporated inventory and transportation decisions into network analysis are reviewed. Table 2.2 presents a categorized overview of recent studies that capture the complexities of BSCs to support decision-making.

Table 2.2. Summary of the most related studies on operational planning of BSCs

Author(s)	Solution approach	Supply chain operations									Risk factor		Environmental impact		
		Replenishment strategy	Coordination mechanism	Biomass pre-processing	Bioenergy conversion	Transportation time windows	Heterogeneous fleet planning	Fleet size	Shipment size	Multi-modal transportation	Logistics operations aspects			Disruption	Operational
											Single Echelon	Multi-echelon			
Aboytes-Ojeda et al. (2020)	2SSP				✓						✓			BQ	
Durmaz and Bilgen (2020)	AHP, GIS and MILP				✓						✓				
Kang et al. (2020)	GIS and MILP				✓						✓				
Akhtari and Sowlati (2020)	MILP and DES										✓			BS, BQ TRR, and PRR	
Nur et al. (2021)	2SSP			✓	✓								✓		
Khoddami et al. (2021)	SD		✓		✓								✓		
Moretti et al. (2021)	MILP			✓	✓						✓				
Ge et al. (2021)	MILP				✓								✓		
Aboytes-Ojeda et al. (2022a)	2SSP				✓						✓			BS	
Aboytes-Ojeda et al. (2022b)	2SSP				✓						✓			BQ	
Gautam et al. (2022)	AHP and MIP										✓				
Nguyen and Chen (2022)	Stochastic mathematical equations	✓									✓			BS and D	
Elaradi et al. (2022)	SP and Monte Carlo			✓	✓				✓				✓	D	
Ko et al. (2022)	SP							✓	✓	✓				BS, TC, and D	✓
Lee et al. (2022)	SP							✓	✓		✓			D and Pr	✓
Salehi et al. (2022)	RO and fuzzy TOPSIS				✓				✓			✓	F	D	✓

Table 2.2 (Continued)

Author(s)	Solution approach	Supply chain operations								Risk factor		Environmental impact	
		Logistics operations aspects								Disruption	Operational		
		Replenishment strategy	Coordination mechanism	Biomass pre-processing	Bioenergy conversion	Transportation time windows	Heterogeneous fleet planning	Fleet size	Shipment size				Multi-modal transportation
									Single Echelon	Multi-echelon			
Aboytes-Ojeda et al. (2022)	SP				✓				✓			BS and BQ	
O'Neill et al. (2022)	SP			✓	✓				✓	✓		BS	✓
Nugroho et al. (2022)	ABS, TEA and LCA	✓			✓		✓	✓	✓	✓		D and PRR	✓
Razm et al. (2023)	LP				✓					✓			
Vazifeh et al. (2023a)	NLP and Game theory		✓		✓						✓		
Muerza et al. (2023)	ABS, AHP, and TOPSIS			✓						✓			
Pandey et al. (2023)	MILP			✓						✓			✓
Piqueiro et al. (2023)	DES and LP			✓						✓			
Umar et al. (2023)	FP and H/M	✓					✓	✓				D	✓
Mondal et al. (2023)	Fuzzy DEMATEL and FP				✓			✓				D, TC, OC, IC, and FC	✓
Chen and Liu (2023)	RO			✓	✓			✓		✓		UE and SS	✓
Kalhor et al. (2023)	RO							✓		✓		D	✓
Lam et al. (2023)	MILP and P-graph			✓						✓			
Samani et al. (2023)	RO and PP							✓			✓	D, Co, and PRR	
Lima et al., (2023)	S-Op			✓	✓		✓	✓		✓		D	
Zarrinpoor and Khani (2023)	FP and fuzzy BWM-TOPSIS							✓				BS, D, and Co	✓

Table 2.2 (Continued)

Author(s)	Solution approach	Supply chain operations									Risk factor		Environmental impact		
		Replenishment strategy	Coordination mechanism	Biomass pre-processing	Bioenergy conversion	Transportation time windows	Heterogeneous fleet planning	Fleet size	Shipment size	Logistics operations aspects		Disruption		Operational	
										Multi-modal transportation	Storage				
											Single Echelon				Multi-echelon
Piqueiro et al. (2023)	MILP and DES							✓				S			
Huang et al. (2024)	SVC-DDRO			✓	✓			✓		✓			BS	✓	
Piedra-Jimenez et al. (2024)	RO			✓	✓			✓					BS, D, and Co		
Darvazeh et al. (2024)	DDRO							✓		✓			BS and Co		
Li et al. (2024)	MILP			✓	✓						✓				
Yunusoglu et al. (2024)	MILP and ML				✓					✓					
Roudneshin and Sosa (2024)	AHP, GIS, and MILP				✓					✓					
Nie et al. (2024)	MILP				✓					✓				✓	
Singh et al. (2024)	LP				✓						✓			✓	
Gital and Bilgen (2024b)	S-Op				✓			✓				S and F	D		
Wang et al. (2024)	Quantile-based MILP and GIS							✓					BS and D		
Ransikarbum and Pitakaso (2024)	MILP and FAHP							✓					BS, D	✓	
Zarrinpoor (2024)	FP				✓		✓	✓		✓			BS, D, Co, Pr and PRR	✓	

Table 2.2 (Continued)

Author(s)	Solution approach	Supply chain operations										Risk factor		Environmental impact	
		Logistics operations aspects										Disruption	Operational		
		Replenishment strategy	Coordination mechanism	Biomass pre-processing	Bioenergy conversion	Transportation time	Heterogeneous fleet	Fleet size	Shipment size	Multi-modal transportation	Single Echelon				Storage Multi-echelon
Gilani and Sahebi (2024)	Fuzzy BWM-MABAC and DDRO				✓		✓		✓				✓	BS and D	✓
Gital and Bilgen (2024b)	S-Op				✓				✓					S and F	D
Wang et al. (2024)	Quantile-based MILP and GIS								✓						BS and D
Ransikarbum and Pitakaso (2024)	MILP and FAHP								✓						BS, D
Zarrinpoor (2024)	FP				✓			✓	✓		✓				BS, D, Co, Pr and PRR
Gilani and Sahebi (2024)	Fuzzy BWM-MABAC and DDRO				✓		✓		✓			✓			BS and D
Li et al. (2025)	MISOCP								✓						BS, D, and PRR
Jabbarzadeh and Shamsi (2025)	RSPP and ML				✓				✓	✓	✓		S		D, Pr and Co
Razm et al. (2025)	DDRO								✓		✓				BS
Huang et al. (2025)	DDRO				✓				✓		✓				D
This Research	Sim and H/M	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	S	BQ, PRR, and TRR	✓

MIP: Mixed-Integer Programming, **MILP:** Mixed Integer Linear Programming; **2SSP:** two-stage stochastic programming, **MSSP:** Multi-stage Stochastic Programming, **FP:** Fuzzy Programming; **RP:** Robust Programming; **TEA:** Techni-Economic Analysis, **LCA:** Life Cycle Assessment; **AHP:** Analytical Hierarchy Process; **GIS:** geographic information systems; **ML:** Machine Learning; **DEA:** Data Envelopment Analysis; **SD:** System Dynamics; **BWM-MABAC:** Best Worst Method-Mult Attributive Border Approximation Area Comparison; **D:** demand; **BS:** Biomass Supply; **BQ:** Biomass quality; **TC:** Transportation cost; **OC:** Operations Cost, **IC:** Inventory Cost, **FC:** Feedstock-related Cost; **Pr:** Price (selling); **PRR:** Process-related; **TRR:** Transportation-related; **Co:** cost; **F:** facility; **S:** Supplier; **UE:** Unit Emissions; **SS:** Social Scores; **H/M:** Heuristic/Metaheuristic; **FP:** Fuzzy Programming; **PP:** Probabilistic Programming; **BWM-MABAC:** Best Worst Method-Mult Attributive Border Approximation Area Comparison; **GIS:** Geographic Information Systems; **LCA:** Life Cycle Assessment; **FAHP:** Fuzzy Analytic Hierarchy Process; **S-Op:** Scenario-based Optimization; **R-MILP:** Robust Mixed-Integer Linear Programming; **MISOCP:** Mixed-Integer Second-Order Cone Programming; **RSPP:** Robust Stochastic Possibilistic Programming

Mathematical programming and optimization techniques provide solutions within specific time periods, where inventory decisions are made for medium-term planning horizons. Variables are optimized through balance constraints that ensure alignment between incoming supply, outgoing demand, and storage capacities at each stage of the SC. These constraints are structured according to an objective function, such as cost minimization, to guide the optimization process and achieve efficient resource allocation. Using linear programming (LP), Razm et al. (2023) developed a production and inventory planning model for bioenergy production that considers age-dependent biomass perishability, storage decisions, and transformation pathways. Their model also accounts for storing biomass as biofuel prior to conversion into bioenergy. Singh et al. (2024) proposed a multi-objective LP model for an animal fat-based biodiesel SC that minimizes cost and environmental impact while maximizing social benefits. The model incorporates supply sites, biorefineries, rendering factories, and distribution depots, and is solved using an augmented ϵ -constraint combined with a lexicographic optimization approach. In another work, Vazifeh et al. (2023a) developed a contract-based coordination mechanism for wood pellet SCs, incorporating quantity discounts and revenue-sharing to resolve conflicting interests among participants. They proposed a bi-level nonlinear programming (NLP) approach using game theory.

In addition to LP and NLP, MILP has been used in several studies to model BSC networks. Moretti et al. (2021) developed a MILP model that accounts for multiple biomass feedstock types, various transportation options, and feedstock pre-processing, while addressing inventory-related decisions. Ge et al. (2021) developed a model for optimizing cellulosic biofuel SCs, incorporating multiple conversion pathways within biorefineries. Similarly, Li et al. (2024) evaluated how different preprocessing and conversion technologies influence the production of sustainable aviation fuel from logging residues. Using MILP, Pandey et al. (2023) developed a county-level SC model to assess the economic and environmental performance of pelleted and baled corn stover for ethanol production, comparing facility locations, capacities, and biomass availability scenarios. More recently, Nie et al. (2024) proposed a model to optimize the selection of biomass production regions, storage depot and biorefinery locations, and storage quantities, while accounting for marginal land availability and region-specific feedstock growth. Beyond standalone MILP, several studies have integrated other techniques, such as the AHP (Gautam et al., 2022), GIS (Kang et al., 2020), combined GIS and AHP (Durmaz and Bilgen, 2020; Roudneshin and Sosa, 2024), P-graph (Lam et al., 2023), ML methods (Yunusoglu et al., 2024), and hybrid DEA-ML approach (Jabbarzadeh and Shamsi, 2025) with MILP to enhance modeling capabilities. In these frameworks, facility location decisions are first identified using the respective techniques, and the resulting

outputs are subsequently incorporated into the optimization models to determine optimal inventory and related operational variables.

Beyond optimization approaches, simulation models have been developed in BSC studies to capture dynamic behaviours and operational complexities. Khoddami et al. (2021) modeled a BSC network using SD to analyze the accumulated stock and flow dynamics of inventories within facilities. Elaradi et al. (2022) developed a MSSP model, to optimize inventory and investment decisions of integrating forest biorefineries in Canada, while accounting for uncertain bioproduct demand using scenario tree and Monte Carlo simulation. In another study, Nugroho et al. (2022) evaluated the economic feasibility and environmental sustainability of methanol production pathways, focusing on production and inventory decisions through an integrated ABS-TEA-LCA approach. Muerza et al. (2023) examined the feasibility of an integrated biomass logistics center in Spain by combining multi-criteria supplier selection methods (i.e., AHP and TOPSIS) with multiproduct transformation processes, while modeling ordering and inventory decisions through ABS.

While deterministic models provide baseline, researchers have developed stochastic approaches to incorporate multiple sources of uncertainty in decision-making processes. Stochastic programming (SP) has been widely adopted to solve non-deterministic mathematical programming models by incorporating the probability distribution of uncertain parameters (e.g., demand, supply, and price). The approach seeks optimal decisions under the assumption that probability distributions are known or can be estimated in advance. These distributions may be continuous, often involving a single uncertain parameter estimated from historical data, or scenario-based, depending on the problem setting (Habibi et al., 2023a). Nur et al. (2021) proposed a 2SSP model for designing a biofuel SC network with biomass quality considerations. Their analysis examined how time and weather-dependent variations in biomass quality influence network design and inventory management. Elaradi et al. (2022) proposed a multi-stage SP model for designing integrated forest biorefineries under uncertain bioproduct demand and evaluated their approach using Monte Carlo simulation. Ko et al. (2022) developed a multi-objective SP model for sustainable biomass transportation network design. Four uncertainty scenarios, based on bioenergy plant's annual capacity and transportation distance were examined to assess the effect of model selection on single- and multimodal transportation modes. Similarly, Lee et al. (2022) proposed a SP model for designing an optimal global biodiesel SC under the demand and price uncertainty, while accounting for fleet size considerations.

In addition to SP, robust optimization (RO) has been applied to address uncertainty, particularly when probability distributions of uncertain parameters are unavailable or difficult to estimate. By focusing on worst-case scenarios, it provides solutions that are less vulnerable to uncertainty and preserve network structure, while maintaining its efficiency and consistent performance (Kalhor et al., 2023). Salehi et al. (2022) developed a robust optimization (RO) model to design a resilient and sustainable BSC network, while considering demand uncertainty and facility disruption. They identified and prioritized critical resilience factors using fuzzy TOPSIS and incorporated high priority ones within the optimization model. In addition to traditional RO, machine learning techniques has led to developing several extensions such as data-driven robust optimization (DDRO) models (Darvazeh et al., 2024; Razm et al., 2025; Huang et al., 2025), support vector clustering-based DDRO (SVC-DDRO) model (Huang et al., 2024), integrated SCV and k-means DDRO (Darvazeh et al., 2024) as well as globalized robust goal programming model with inner-outer sets (Chen and Liu, 2023). Unlike traditional RO, which often yields conservative solutions, DDRO derives uncertainty sets from historical or simulated data, capturing realistic variability and correlations to produce more balanced and practically applicable solutions.

Fuzzy modelling has also been applied in the literature (Umar et al., 2023; Mondal et al., 2023; Zarrinpoor, 2024) as a practical approach for handling situations where precise parameter values are unavailable, reflecting epistemic uncertainties. In such cases, uncertain parameters are represented through possibilistic distributions, which allows decision-makers to incorporate vagueness and imprecision into the modeling process and generate more flexible solutions. In addition to mathematical programming techniques, simulation approaches such as ABS (Nugroho et al., 2022), discrete-event simulation (DES) (Akhtari and Sowlati 2020; Piqueiro et al., 2023), and Monte Carlo simulation (Elaradi et al., 2022) have been employed to address various sources of uncertainty through what-if scenario analysis, while evaluating their impacts on network operations. This approach provides a flexible framework for modeling variability and recovery strategies, enabling the incorporation of high degree of complexity into the problem. While optimization models generate prescriptive solutions for specific scenarios, simulation offers decision-makers the opportunity to explore system behavior under diverse conditions and assess responses to alternative inputs (Saisridhar et al., 2024). Moreover, integrated approaches combining MCDM techniques, mathematical programming, and machine learning algorithms have been advanced to tackle storage and transportation challenges in uncertain environments.

2.3. Research Gaps

Although literature provides valuable information, it suffers from limitations in terms of modeling techniques and SCR measurement metrics, which underscores the need for a more holistic approach. A sudden disruption or unexpected event can quickly propagate its adverse effect downstream echelons and cause a ripple effect (Aldrighetti et al., 2021). Overlooking this phenomenon in SCR analysis may lead to an underestimation of the full impact of disruptions and insufficient preparation for mitigating their consequences. Since quantifying disruption propagation to downstream echelons in SCs is challenging and complex (Hosseini et al., 2020), most studies have not considered it to simplify model implementation. Moreover, the employed measures might not fully depict the system's resilience, as they typically concentrate on only one or two resilience capacities and may not be generalized to all types of SCNs. Moreover, in the studies of Table 2.1, the recovery strategies are activated within the predefined time period. However, this assumption may not always reflect the unpredictable nature of disruptions in real-world scenarios.

From the operational planning perspectives, while single-echelon inventory planning provides insights into isolated segments, it fails to capture the inherent complexity and interdependencies of multi-echelon SCs (Fokouop et al., 2024; Claassen et al., 2024). In such networks, decisions made at higher echelons, such as inventory allocation can have cascading impacts on everything from production schedules to customer delivery times (Vieira et al., 2023). Although previous research has highlighted the importance of inventory management either in bio-hubs or biorefineries, it often lacks depth in exploring advanced inventory policies within the BSC context (Jazinaninejad et al., 2022). Proper inventory control can enhance SC efficiency by optimizing replenishment schedules, preventing overstocking, minimizing stockouts, and ultimately improving demand fulfillment (Ivanov et al., 2021). From the logistics planning perspective, the literature remains focused on shipment size determination and inventory balance constraints that capture only a limited portion of SC dynamics. Key aspects of transportation planning, including fleet sizing, heterogeneous fleet deployment, and the integration of multimodal transport networks have not been studied sufficiently. Yet, these elements are critical in real-world systems, where trucks, ships, and rail should be coordinated under capacity, routing, and scheduling constraints. The perishability of biomass further underscores the importance of robust logistics design, as quality degradation during storage and transportation directly reduces energy

yield and raises costs. Preprocessing operations such as drying, densification, and chipping can mitigate these losses and improve feedstock quality; however, their integration into optimization models remains limited (Valipour et al., 2024). At the coordination level, existing approaches often fail to align tactical planning with operational realities, where long-term facility utilization and transport configurations must adapt to real-time disruptions, seasonal variability, and infrastructure limitations (Ebrahimi et al., 2025).

In terms of modeling, existing studies have not adequately addressed the inherent uncertainties in real-world BSCs, where the interdependence of components significantly influences real-time decision-making. In addition to disruption risks, operational risks are prevalent in SC activities that impact real-time decisions (Zhang et al., 2024). These risks are not only common but also deserve significant attention because they happen frequently, unlike disruption risks. Therefore, taking into account both types of risks in planning the SC activities can lead to developing comprehensive risk management strategies and ensuring the SCR. Despite its importance, previous studies often overlook such variabilities, mainly at the operational level, as exact function evaluations using traditional techniques can be costly or impractical when multiple sources of uncertainty are involved. The efficiency of the proposed stochastic programming techniques is compromised by challenges in accurately estimating the probability of rare events, excluding unknown events and considering the direct effects of risks solely without considering their propagation and indirect impacts (Ivanov and Dolgui, 2019; Vieira et al., 2023).

To overcome these limitations, this study introduces several methodological and conceptual advancements aimed at enhancing the resilience, adaptability, and coordination of BSCs under uncertainty.

Chapter 3: Key Enablers of Biomass Supply Chains

3.1. Introduction

The record levels of CO₂ concentration in the atmosphere, resulting from fossil fuel use, pose a troubling increase in health and environmental risks linked to climate change (IEA, 2022a). In addition, the world is dealing with rarely seen energy security challenges due to conflicts and political instabilities, leading to uncertainties in energy supply and pricing. A solution to these problems is a global shift towards cleaner, renewable energy sources while ensuring affordable and secure energy services. Given this motivation, retrieving valuable resources from waste materials is gaining importance. This practice is essential for building a sustainable and circular economy, preserving ecosystems, and decreasing reliance on finite natural resources (Vitale et al., 2022). Accordingly, the transformation of biomass into bioenergy has attracted significant interest among academics and industries (Zahrae et al., 2020). Biomass is the primary global renewable energy source, contributing to 55% of the total renewable energy supply (IEA, 2022b). It constituted approximately 10% of the world's overall energy sources in 2019, and it is predicted to double by 2030 (Jazinaninejad et al., 2022). In fact, the wide range of biomass available worldwide renders this form of energy accessible at an affordable price. Bioenergy production includes interconnected processes of biomass sourcing, processing, storage, distribution, and conversion, which are known as a biomass supply chain (BSC). As such, realizing the potential growth of bioenergy depends on establishing meticulously devised BSCs that are productive and environmentally conscious (Helal et al., 2023). Figure 3.1 illustrates the activities and interconnected relationships between the operations within a generic BSC, where arrows show possible transportation between operations.

Bioenergy can be derived from various feedstock sources, such as agricultural residues, forestry residues, energy crops, and organic waste, which, unlike fossil fuels, are geographically scattered. Some sources of biomass feedstock, such as agricultural residues, may not be accessible all year round or may vary considerably in supply over time (Ekşioğlu and Klein, 2015). The key factors that hold significant importance in biomass utilization for energy purposes, especially forestry residues, are heating value, moisture content, and ash content (Gautam et al., 2017). Heating value signifies the energy released by biomass when it undergoes combustion, while

moisture content is defined as the amount of water contained within the feedstock (e.g., wood). Ash content, on the other hand, represents the proportion of inorganic substances found in biomass. These three attributes are interconnected and subject to change over time (Peter, 2002). Hence, the net energy produced by biomass can be influenced by its moisture content because of energy utilization in vaporizing water during combustion (Gautam et al., 2017)

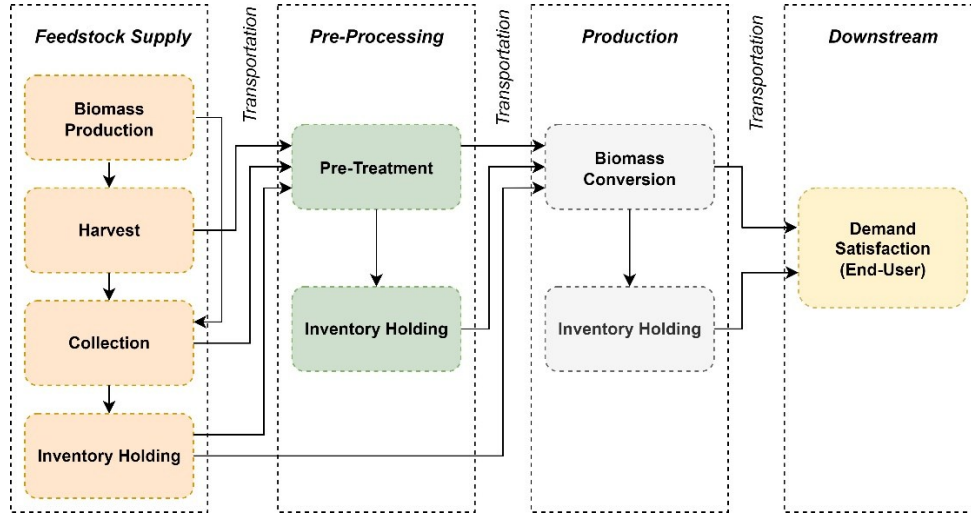


Figure 3.1. Activities and operational relationships in BSC (adopted from Jazinaninejad et al., 2022)

Additionally, the presence of ash in biomass decreases the overall net energy. Consequently, these characteristics can influence biomass procurement costs (Pettersson and Nordfjell, 2007). Furthermore, as the largest contributor to worldwide bioenergy production, the forestry industry presents logistical challenges due to its bulkiness and varying quality characteristics (Gautam et al., 2017). Typically, this results in additional costs for equipment and transportation, potentially leading to increased environmental harm to the environment. Indeed, transporting equipment over long distances solely for feedstock procurement is generally not profitable (Alam et al., 2012). Moreover, access roads constructed within forests often need to be more resistant and deteriorate soon after they are built. Since residual forest biomass is a low-value by-product of the logging industry, it may not be financially justifiable to invest in road improvement exclusively for its procurement. Moreover, weather constraints during certain seasons (e.g., winter) can interrupt transportation operations, while heating demand is typically higher during winter (Gautam et al., 2017). These issues highlight a pressing need to find a feasible solution in establishing and/or

scaling up bioenergy production and fostering the sustainable growth and development of the bioenergy sector.

One possible solution to these problems is establishing an intermediary hub between suppliers (e.g., forests) and end users (e.g., biorefineries). A hub acts as an intermediary location where farmers and growers can deliver their by-products (e.g., straw and harvesting residues) for processing into value-added commodities (e.g., dried wood and pellets), which are crucial for bio-based projects (Kulišić et al., 2019). As a result, a variety of biomass types could be consolidated in a single location leading to streamlining the processing and storage activities of feedstock (Nguyen et al., 2020). Bio-hubs offer an opportunity for biomass suppliers to maintain their production during off-season periods and enable companies to connect and trade with one another. Furthermore, these hubs can serve as capital markets for feedstock, providing contractual advantages for stakeholders along the supply chain (Nasso et al., 2020). Therefore, bio-hubs could become a key enabler in facilitating the effective mobilization of bioresources on a large scale. All these endeavors stemming from bio-hub implementation can result in a decrease in seasonal variations in supply and can enhance biomass availability throughout the year (Rai and Monaghan, 2024). Drawing from experiences in Sweden, bio-hubs contribute to the advancement of the bioeconomy despite potential challenges such as increased product demand and the need for infrastructure sharing within hubs. Hence, bio-hub incorporation could help Sweden to reduce its dependence on foreign resources and achieve its target of relying entirely on renewable energy by 2040 (Nasso et al., 2020).

Furthermore, concentrating the transportation operations in one centralized location rather than dispersing them across various supply points, could improve uninterrupted access to feedstock year-round. This is particularly crucial in addressing challenges associated with interruptions in feedstock transportation from fields during certain seasons due to weather restrictions (Gautam et al., 2017; Gautam et al., 2022). Moreover, strategically located bio-hubs could offer the opportunity to have access to various transportation modes such as road, rail, and water transport, thus enhancing transportation efficiency (Aboytes-Ojeda et al., 2022b). As such, bio-hubs play a critical role in achieving a BSC's objective of delivering standardized feedstock to customers in a timely manner and at an affordable price (Kons et al., 2014). Despite its significant advantages, implementing bio-hubs in the context of the BSC presents challenges related to capital investment, operating costs, feedstock availability, and environmental considerations. Hence, careful and

comprehensive planning is essential to ensure the successful establishment and operation of bio-hubs within BSCs.

In the BSC literature, researchers have proposed several models aimed at facilitating effective decision-making related to various aspects of actors in a supply chain (SC). There are some interesting review papers in this field, such as the recent works of Zahraee et al. (2020), Mottaghi et al. (2022), Jazinaninejad et al. (2022), and Habibi et al. (2023a). While these papers have delved into BSCs with a focus on sustainability and uncertainty considerations, a notable gap exists in the specific examination of key actors, such as bio-hubs. Therefore, this study aims at providing insights into how scholars/practitioners can identify and adopt the best-fitting approaches to overcome the potential challenges of bio-hub implementation. We investigate the existing literature comprehensively to categorize the previous studies considering several aspects including the characteristics of the problem, sustainability pillars, and methodology. A holistic understanding of these aspects can offer valuable insights into BSC management while incorporating bio-hubs. This knowledge is critical in optimizing processes, enhancing efficiency, and identifying areas for improvement. Moreover, by scrutinizing the challenges faced by bio-hubs, researchers and practitioners can develop targeted strategies and solutions to mitigate potential bottlenecks, ensuring the resilience and sustainability of BSCs. This literature review bridges the existing gaps by focusing exclusively on integrating bio-hubs within BSCs, shedding light on comprehensive considerations demanded by this relatively new paradigm. Furthermore, this research seeks to not only consolidate existing studies but also identify trends and emerging perspectives, which can help make informed decisions. Therefore, the findings can be valuable for scholars, policymakers, and industry stakeholders seeking guidance in navigating the complexities of implementing bio-hubs in BSCs. To this end, a five-step guideline of Denyer and Tranfield (2009) is followed to implement a systematic literature review (SLR) within the last ten years.

The remaining contents of this review are as follows. Section 3.2 provides an explanation of the bio-hub concept and its economic, environmental, and social advantages. Then, the implementation challenges are discussed. In Section 3.3, the research methodology, research questions, and the selection criteria of the articles are explained. The results and conclusions of the in-depth analysis are presented in Section 3.4. Section 3.5 discusses future research opportunities, followed by Section 3.6, which summarizes the results.

3.2. Background

3.2.1. The Bio-Hub Concept

A significant part of the bioenergy industry relies on traditional BSCs involving direct transportation from harvest sites to other facilities (e.g., a mill). This system involves the procurement of biomass feedstock through contractual arrangements with local growers (Lamers et al., 2015b). Subsequently, these feedstock are harvested, stored within proximity, and transported in bales or low-density bulk forms to the conversion facilities (Eranksi and Dale, 2011). However, the conventional approach poses significant logistical and handling challenges, mainly feedstock with high moisture content (e.g., forest-based biomass). Using such a feedstock can result in the reduction of the effective payload of trucks and consequently decrease the economic and environmental sustainability of BSCs (Strandgard et al., 2021). Furthermore, storing high moisture feedstock for a long time may pose a substantial risk of biomass losses and decrease the heating value, resulting in economic significance (Routa et al., 2018). This leads to quality and quantity reduction and contributes to the undesired proliferation of fungal spores within biomass piles (Barontini et al., 2014). Also, in extreme self-ignition cases, the stored feedstock might be completely destroyed (Li et al., 2006). Finally, when stored in open yards, biomass is exposed to uncontrollable factors such as rain, ice, and wind (Toscano et al., 2022).

Recently, numerous studies have focused on tackling these challenges, proposing a new SC concept under various terms (e.g., hub, depot, and terminal). While these terms may vary across different research endeavors, their core functions remain consistent and can collectively be referred to as "bio-hub." This concept draws inspiration from the idea of advanced uniform feedstock design systems (Hess et al., 2009). The advanced system introduces strategies to create a product with higher density and efficiency while mitigating degradation rates. These tactics could range from simple mechanical actions such as crushing, chipping, shredding and grinding, bundling and baling, screening/sieving/sorting and mixing or more intricate processes like ensiling, storing, drying, pelletization, torrefaction, and pyrolysis (Gold and Seuring, 2011). Such strategies could be implemented in bio-hubs to change the physical characteristics of feedstock, such as bulk densities and moisture content, depending on the input by-product and desired output (Keith and Castillo-Villar, 2023). These processes transform biomass into a standardized format, enabling it to be treated as a commodity that can be traded in the market (Bui et al., 2023). By standardizing the material format, biomass becomes more readily available to biorefineries, facilitating

continuous and consistent supply to large-scale facilities in an economically viable manner (Hess et al., 2009). Indeed, these commodities serve as intermediary products that have uniform physical and chemical attributes, improving flowability, transportability (i.e., reduced bulk density), and storability (i.e., reduced moisture content and particle size) of feedstock (Keith and Castillo-Villar, 2023). This consistency enables the use of a similar supply system infrastructure for all biomass resources, making it compatible with existing high-capacity handling and transportation systems and equipment (Lamers et al., 2015a). It is worth mentioning that challenges related to variable properties of bulk solids during feeding and handling can result in a reduction in plant throughputs of up to 50%, thus significantly impacting biorefinery efficiency (Lamers et al., 2015b). Figure 3.2 demonstrates an example of bioproduction pathways for forest biomass processing in bio-hubs.

According to Lamers et al. (2015a), depot (i.e., bio-hub) facilities can be categorized into two types: standard and quality facilities. The standard facility focuses on pelletizing cellulosic feedstock (e.g., wood and agricultural residues) to enhance its quality for transportation and storage. On the other hand, the quality depot not only pelletizes but also pre-treats the feedstock for specific downstream utilizations, such as biorefinery or animal feed (Kim et al., 2018). While the depot-based decentralized approach incurs additional costs for pre-treatment and pelletization, the improved shipping logistics and bulk density lead to significant economies of scale, ultimately offsetting these extra costs and reducing transport expenses compared to the centralized system (Kim and Dale, 2016).

3.2.2. Economic, Environmental, and Social Aspects of Bio-Hub Implementation

Bundling of supply quantities and creating distribution hubs/terminals have been proposed and practiced in managing SCs in manufacturing, agriculture, and service sectors. In the case of biomass, however, there is still a need to further implement such hubs across the globe, particularly in jurisdictions with vast geography and those with a considerable number of remote communities (Mafakheri et al., 2021). Their strategic placement, efficiency, and integration with various bioenergy sources can significantly impact the sustainability and economic viability of bioenergy production (Lautala et al., 2015).

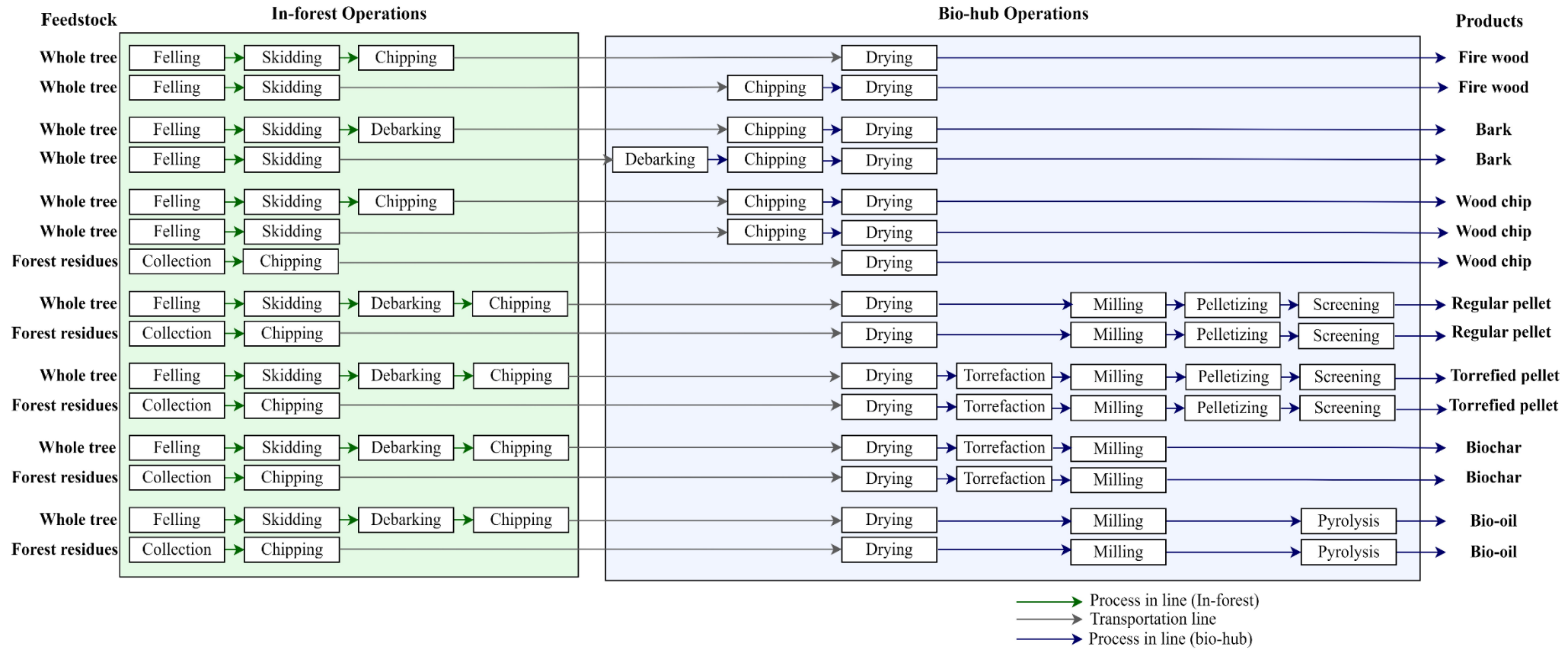


Figure 3.2. A schematic of bioproduction pathways for forest biomass in a bio-hub (adopted from Pradhan et al., 2022)

According to International Energy Agency (IEA), bio-hubs can mitigate large amounts of financial risks related to feedstock supply and address challenges associated with quality, quantity, and consistency of supply. This, in turn, can facilitate access to capital budgeting, expedite project financing, and enhance policy effectiveness in bioenergy production (Nasso et al., 2020). Also, implementing bio-hubs can have indirect cost benefits by increasing supply security, economies of scale, and price stability (Virkkunen et al., 2016; Aboytes-Ojeda et al., 2022b).

From the environmental perspective, bio-hubs can reduce greenhouse gas (GHG) emissions associated with transportation through logistics optimization and biomass resource consolidation (Muerza et al., 2023). Indeed, strategically placing bio-hubs not only minimizes environmental impact but also helps reduce wildfire risk by managing biomass resources in supply areas like forests (Nicholls et al., 2022). Additionally, centralizing preprocessing activities at bio-hubs enables more efficient waste management and promotes sustainable practices. The establishment of bio-hubs in the BSC also brings notable social benefits. These include creating employment opportunities within local communities and fostering economic growth and stability. Moreover, bio-hubs can contribute to community engagement and collaboration, encouraging partnerships among various stakeholders, such as local businesses and cooperatives (Kulišić et al., 2019). Last but not least, these hubs can act as consolidated and reliable feedstock suppliers, offering contractual advantages for actors in a BSC (IEA, 2021).

3.2.3. Challenges Associated with Bio-Hub Implementation

As discussed, the successful implementation of bio-hubs in BSCs presents a promising avenue for optimizing bioenergy production; however, it comes with its own challenges requiring careful consideration. These challenges range from economic uncertainties surrounding initial investments to intricate social and policy frameworks. Below are some of the main problems associated with establishing bio-hubs.

1. High Initial Investment and Operating Costs: Establishing bio-hubs involves considerable costs, including infrastructure development and technology adoption, which may pose financial challenges. In addition, the operational costs of a bio-hub can significantly impact its economic feasibility, affecting its profitability and long-term viability. Each operational step in the bio-hub incurs specific expenses, contributing to the total cost of processing biomass feedstock. Such operating costs include a wide range of factors, such as energy consumption, maintenance of

machinery, labor costs, and logistical considerations. Efficient management of these cost factors, which are as important as the initial investment, is crucial for optimizing the economic viability of a bio-hub (Muth et al., 2014; Gautam et al., 2022).

2. *Location Selection*: Identifying a suitable location for bio-hubs is complicated. It should be strategically situated to minimize overall cost, be accessible for feedstock suppliers, end users, and logistical infrastructure (e.g., rail ramps, in-land ports, and seaports), and address environmental and social considerations (Berg and Athanassiadis, 2020a; Toba et al., 2023).

3. *Land Availability*: Securing suitable and adequate land for facility establishments such as bio-hubs can be challenging, especially in areas with high land demand for agricultural and/or residential purposes (Miguéis et al., 2022; Roy and Tu, 2022).

4. *Ownership*: The organizational structure and ownership of a bio-hub can affect business strategies. Bio-hubs might be controlled by other actors within BSCs (e.g., biorefineries). As such, cooperative models could be adopted to integrate bio-hubs with upstream and/or downstream actors of BSCs. Furthermore, bio-hubs can operate as standalone markets. These hubs are expected to function autonomously in this scenario, operating as financially independent and efficient business entities (Lamers et al., 2015b; Mafakheri et al., 2021; Nicholls et al., 2022).

5. *Biomass Availability*: The size and technical layout of a bio-hub will be influenced by the availability and seasonality of feedstock (Castillo-Villar et al., 2017). In addition, a flexible and reliable biomass supply is necessary for bio-hubs to operate all year. Furthermore, seasonality and weather conditions can lead to variations in availability and potential disruptions in feedstock supply (Lamers et al., 2015b; Soren and Shastri, 2019).

3.3. Review Methodology

To assess the current research landscape and consolidate scholarly efforts regarding the implementation of bio-hubs, an SLR within this domain is conducted. An SLR is a rigorous and structured approach to analyzing existing research in a particular field. It involves the predefined process of searching, evaluating, and synthesizing relevant studies to answer specific research questions or address particular objectives. Hence, an SLR helps researchers comprehensively survey the available body of knowledge on a particular topic, providing a solid foundation for

building new research or making informed decisions. It ensures transparency and reproducibility in the review process by clearly documenting the search strategy and inclusion/exclusion criteria, enhancing its credibility (Han et al., 2020). Accordingly, this study follows the five-step guideline of Denyer and Tranfield (2009) to implement the SLR. This methodology has also been adopted by other literature review studies, such as Ali et al. (2017), Han et al. (2020), and Llaguno et al. (2022). These steps are as follows (Denyer and Tranfield, 2009).

I) Formulating the research question(s): The first critical step in conducting an SLR is meticulously defining the study's scope. This includes establishing the boundaries of the research and pinpointing the specific research questions that will provide direction throughout the review process. As such, researchers lay a solid foundation for a well-structured and purposeful SLR. Regarding the explanations given in the previous section, the primary goal of this study is to assess the impact of integrating bio-hubs in BSCs by addressing the following research questions:

Q1: What key levels of analysis and decision-making are addressed in the literature?

Q2: What methodologies and metrics have been employed in assessing bio-hub implementations, and how do these methodologies influence research outcomes?

Q3: What recommendations can be drawn from the literature to enhance the successful integration of bio-hubs within the BSC?

II) Searching and identifying core studies: There are arguably two major abstract and citation databases, i.e., Web of Science (WOS) and Scopus, that collectively cover nearly 95% of all research publications, providing a comprehensive information base (Spieske and Birkel, 2021). To maintain impartiality and comprehensiveness, these two databases were utilized to retrieve articles published in internationally peer-reviewed journals. All studies published within the ten-year period preceding the end of March 2024 are covered. To identify and list core papers related to the review questions, as per the second step of the adopted guideline, it is necessary to establish an initial set of keywords. To have a comprehensive list of keywords, first, a number of highly cited papers were selected based on the current list. By analyzing these influential papers, researchers can identify common themes, concepts, or terminologies frequently used in the field, contributing to the comprehensiveness of the keyword list. Then, their keywords and derivatives were added to the initial list of keywords to find relevant articles. These steps were repeated to expand the keyword list until it reached a stage encompassing all commonly used keywords. It is worth

mentioning that the query was used to explore the database with a focus on the titles, abstracts, and/or keywords of the publications. The final list of keywords is as follows, where similar terms are grouped within the same category using the Boolean operator “OR” and the Boolean operator “AND” combines these three categories.

(hub OR terminal OR depot OR yard OR “distribution facility” OR “storage facility” OR “distribution center(re)” OR “storage centre(re)” OR “preprocessing facility” OR “pre-processing facility” OR “pretreatment facility” OR “pre-treatment facility” OR “logistics center(re)” OR “collection centre(re)” OR “collection facility”) AND (biomass OR bio-mass OR bioenergy OR bio-energy OR biofuel OR bio-fuel OR bioethanol OR bio-ethanol OR biogas OR bio-gas OR biodiesel OR bio-diesel OR “bio oil” OR bio-oil OR biorefinery OR bio-refinery) AND (“supply chain” OR “supply-chain” OR logistics)

III) Selecting related papers: After listing initial articles given the defined search query and the criteria established in the preceding stages, a thorough evaluation is essential. In total, 158 and 144 records were found in WOS and Scopus, respectively. It is noteworthy that the removal of keywords related to bio-hubs (e.g., hub, terminal, depot, distribution center, storage center, and yard) would result in publication counts of 2955 and 3581, respectively. This substantial difference underscores that a relatively small portion of the papers addressing BSCs have explicitly integrated the concept of bio-hubs. Before the comprehensive evaluation of the sources found in the previous step, duplicates were identified and removed to avoid redundancy in the review process. Afterwards, the titles and abstracts of the remaining articles underwent a screening process based on the exclusion and inclusion criteria to maintain the transparency of the process. This step excludes studies that do not meet the predetermined inclusion conditions. The review process of this study considers peer-reviewed journal papers (i.e., published, in-press, and pre-publication versions) written in English about bio-hub implementation problems in BSCs. As such, conference papers are excluded from this study because of their limited accessibility and different review procedures (Habibi et al., 2023a). Also, these conditions required that the articles specifically state their research objectives as quantitative investigation or assessment of the decisions, effects, benefits, or challenges associated with bio-hub implementation in BSCs. These criteria have been listed in Table 3.1. By examining the abstracts, the selected articles for additional full-text review are identified.

Table 3.1. Review exclusion and inclusion criteria adapted from Ghobakhloo (2020) and Iftikhar et al. (2024)

Category	Criteria	Description
Exclusion	A	Any article not characterized as a peer review article (e.g., conference papers, book chapters, notes, books, and thesis/dissertations)
	B	Any article without full text
	C	An article not written in English;
	D	Any article that did not implement a quantitative investigation or assessment associated with bio-hub implementation in a BSC
Inclusion	A	Any article which is peer-reviewed and formally accepted for publication
	B	Bio-hub implementation in the context of a BSC must be the core focus of the article
	C	A quantitative methodology was used for modelling and analysis

Following that, the full text of the articles was evaluated to ensure the quality and relevance of the papers remaining. Moreover, the reference lists of the short-listed papers were thoroughly scrutinized based on the inclusion and exclusion criteria to make sure that no other relevant articles were inadvertently excluded during the search process. As a result, 212 papers were eliminated due to duplication, insufficient discussion of results, and lack of transparency in concepts and ideas. Finally, this comprehensive examination resulted in 90 journal articles to conduct more in-depth analyses in line with the last two steps outlined in the adopted guidelines. These steps include analysis and synthesis of findings, as well as the presentation of results followed in the next sections. Figure 3.3 illustrates the summary of steps taken to identify the shortlisted papers.

3.4. Research Findings

In this section, descriptive and quantitative analyses are conducted to have a deep understanding of the shortlisted papers. These publications are investigated in terms of their journals and geographical distribution in the descriptive analysis subsection. Then, they are categorized and examined in-depth from modeling and input-output perspectives.

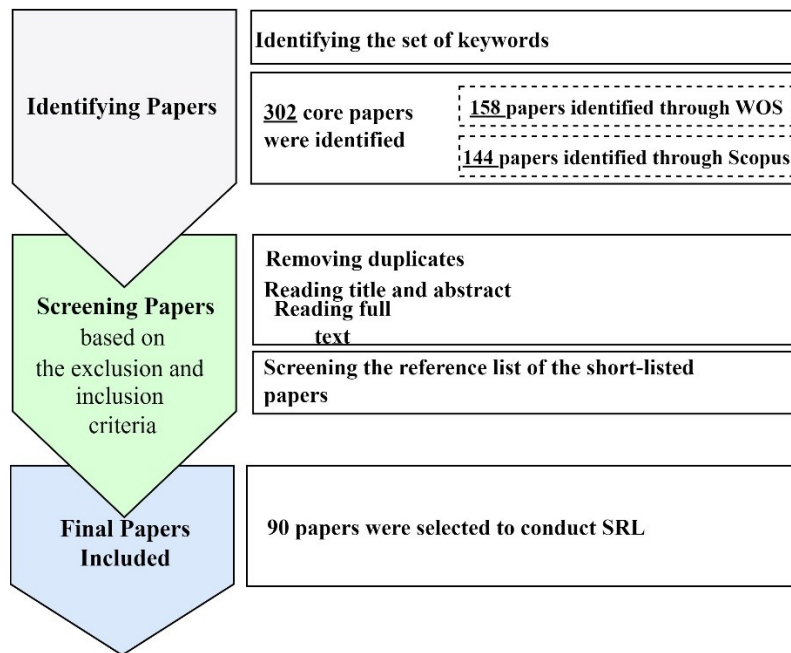


Figure 3.3. Review process of finding suitable papers in the SLR

As discussed in the preceding sections, several terms have been used to refer to the bio-hub concept. Findings indicate that “depot”, “terminal”, and “hub” are more commonly adopted than the other ones. Based on the descriptions provided in these studies, it seems that “terminal” is predominantly utilized when authors intend to refer to a logistical node where biomass is stored, loaded, and often chipped for subsequent transportation activities. However, alternative terms are frequently employed when implementing more complex processes, such as drying and pelletization. It should be noted that these terms are used interchangeably throughout this study. Table 3.2 illustrates the frequencies of the bio-hub terms.

Table 3.2. The frequency of bio-hub terms

Bio-hub Term	Frequency	Bio-hub Term	Frequency
Depot	36	Terminal	18
Hub	16	Collection center	5
Storage facility	3	Yard	2
Preprocessing facility/center	2	Pre-treatment center	2
Integrated biomass logistics centre (IBLC)	2	Mobile pyrolysis system	1
Regional biomass collection depot	1	Distribution facility	1
Regional biomass preprocessing depot (RBPDP)			1

3.4.1. Descriptive Analysis

The number of papers published in each journal is displayed in Table 3.3. The range of these journals is wide and includes 42 journals. Notably, the journals “*Applied Energy*”, “*Journal of Cleaner Production*”, “*Biomass and Bioenergy*”, “*Energies*”, “*Biofuels, Bioproducts and Biorefining*”, “*Bioresource Technology*”, and “*GCB Bioenergy*” hold the largest share and contributed nearly 50% of the publications. Also, the geographical distribution of papers worldwide was extracted based on the authors’ affiliation, shown in Figure 3.4. The degree of color in the visualization denotes each country’s contribution level. A total of 25 countries were included in the literature, with the United States of America (USA) and Canada emerging as the leading contributors.

Table 3.3. Distribution of journals and published papers

Journal	No. of Papers	Journal	No. of Papers
Applied Energy	10	Journal of Cleaner Production	7
Biomass and Bioenergy	7	Energies	5
Bioresource Technology	4	Biofuels, Bioproducts and Biorefining	4
GCB Bioenergy	4	Computers & Industrial Engineering	3
Transportation Research Part E: Logistics and Transportation Review	3	Annals of Operations Research	3
Renewable Energy	3	IISE Transactions	3
Sustainability	2	Forests	2
ACS Sustainable Chemistry & Engineering	2	Scandinavian Journal of Forest Research	2
International Journal of Production Research	1	Renewable and Sustainable Energy Reviews	1
Applied Mathematical Modelling	1	Energy	1
Chemical Engineering Transactions	1	Energy Technology	1
Clean Technologies and Environmental Policy	1	IEEE Transactions on Evolutionary Computation	1
Computers & Chemical Engineering	1	Frontiers in energy research	1
The International Journal of Life Cycle Assessment	1	Environmental Management	1
International journal of energy research	1	Annals of Forest Research	1
Mathematics	1	Sensors	1
International Journal of Forest Engineering	1	Canadian Journal of Forest Research	1
International Journal of Chemical Reactor Engineering	1	Environmental Science and Pollution Research	1
Biosystems Engineering	1	Renewable Energy Focus	1
Sustainable Energy Technologies and Assessments	1	BioEnergy Research	1
Transportation Research Record	1	Sustainable Production and Consumption	1

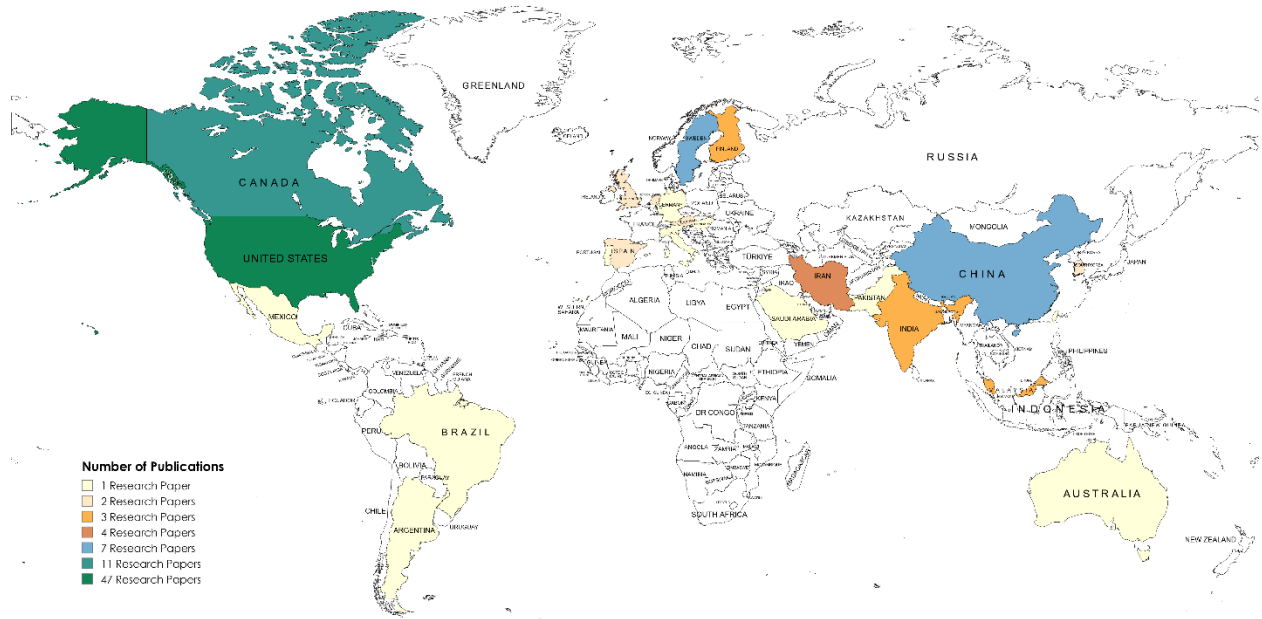


Figure 3.4. The spatial spread of participating countries

3.4.2. Quantitative Analysis of Bio-Hub Implementation

To address challenges associated with bio-hub implementation in BSCs, some researchers have focused on real-world studies and case examples. This section examines the main features of the selected papers (e.g., objectives and decision variables), along with their findings. To streamline studies focusing on similar aspects of incorporating bio-hubs, papers are categorized based on their modeling approaches, including mathematical programming, simulation, multi-criteria decision-making (MCDM), and systematic modeling. Indeed, each set of modeling methodologies proves effective in addressing specific facets of bio-hub integration. Within each category, the specific focus of each study and its significance are discussed in the following sections.

3.4.2.1. Mathematical Programming

A prevalent trend in the literature reveals the widespread application of mathematical programming, constituting 70% of the papers published (i.e., 64 out of 90). This category includes mixed-integer programming, linear programming, non-linear programming, stochastic programming, fuzzy programming, and P-graph modeling. These studies examine strategic (long-term), tactical (mid-term), and operational (short-term) decisions, which collectively contribute to

the understanding of how hub implementation impacts BSC performance. A comprehensive summary of these studies has been provided in Table A1 in Appendix A.

According to this table, scholars have primarily focused on strategic decisions at the upstream level, mainly determining the optimal location and number of bio-hubs, along with their allocation to diverse resources and markets. Establishing a bio-hub requires a significant investment of time and financial resources, making it challenging to alter decisions once made (Gautam et al., 2022). As such, evaluating the economic feasibility of these facilities during the planning phases is of cardinal importance (Martinkus et al., 2018). This issue is clearly evident from Table A1 since the primary objective across all these studies was optimizing economic factors. These factors include minimizing the total cost of bio-hubs (e.g., capital cost, logistics, purchasing, and inventory costs) along with other BSC costs or maximizing the net present value and profit of these hubs. Alongside the economic aspect, minimizing the environmental footprint related to bio-hub implementation, particularly GHG emissions, has been proposed in 11 out of 64 cases. Moreover, maximizing the social objective of job creation was another objective function recognized in 3 out of the 64 cases examined. These factors collectively highlight the importance of sustainable bio-hub planning.

One of the main functions of bio-hubs is to consolidate shipments and consequently reduce the number of direct routes between origin and destination points. Accordingly, improving economies of scale can lead to a decrease in transportation costs (Aranguren et al., 2021). To facilitate the integration of hubs into BSCs, hub-and-spoke models have been proposed (Roni et al., 2014; Roni et al., 2017; Aranguren et al., 2018; Aranguren et al., 2021; Aranguren and Castillo-Villar, 2022; Aboytes-Ojeda et al., 2022b). The hub-and-spoke networks can be helpful in designing large-scale BSCs while minimizing the total cost of the system (Roni et al., 2014). As illustrated in Aboytes-Ojeda et al. (2022b), bio-hubs can reduce transportation costs by efficiently delivering densified biomass over long distances and in large quantities using high-capacity transport vehicles.

In addition to bio-hub location and biomass flow planning (i.e., amount of feedstock transshipped to/from bio-hubs), capacity planning is another important aspect that warrants examination during the BSC design process. Such decisions directly impact the efficiency and resilience of BSCs and responsiveness to supply and demand fluctuations (Salehi et al., 2022; Esmaeili et al., 2023). This issue has been addressed in about 30% of the studies in this category (see Figure 3.5). Some scholars have leveraged the benefits of bio-hub implementation by

optimizing vehicle routing, resource management, technology selection, and production planning of bio-hubs.

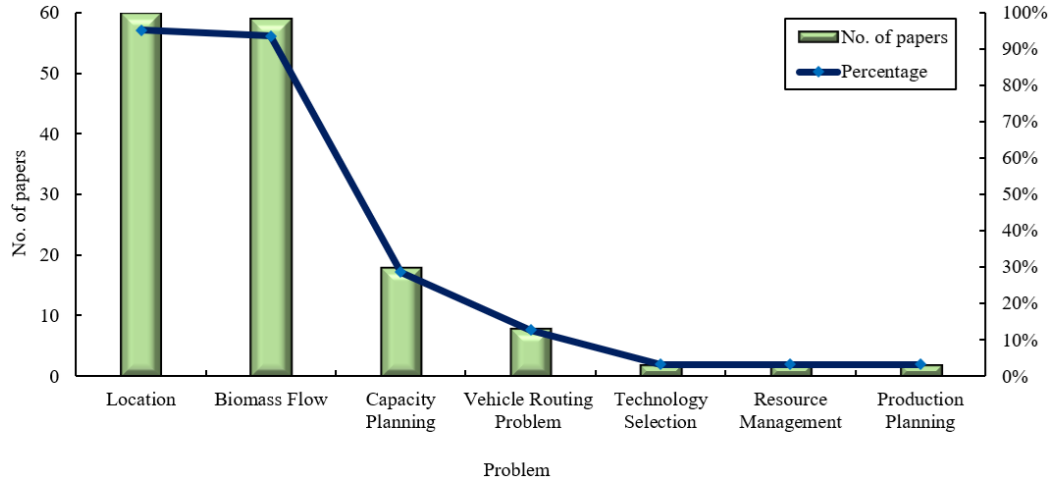


Figure 3.5. The frequency of problems optimized through mathematical programming

Given the inherent uncertainty and disruptions within all SCs, particularly BSCs, ignoring their effects and proposing deterministic models can lead to infeasible or sub-optimal solutions (Habibi et al., 2023a). Results indicate that 30% of papers within this category have considered uncertainty factors such as feedstock quality (e.g., moisture content), feedstock quantity, market demand fluctuation, price, and transportation-related factors (e.g., loading, unloading, and transportation time) in their bio-hub planning problems. In these papers, two-stage stochastic optimization has been mostly used to model problems. In addition to these operational risks (i.e., high frequency and low impact), some researchers highlighted the necessity of planning for disruption risks (particularly for low frequency but high impact disruptions) during the design stage, particularly when implementing capital-intensive facilities such as bio-hubs. Liu et al. (2017) demonstrated the effect of disruption risks on optimal bio-hub locations and supply chain costs. According to Marufuzzaman et al. (2014), when site-dependent probabilistic disruptions (e.g., flooding, hurricanes, and drought) are considered in the planning phase, the model locates hubs in areas with low disruption probabilities. Maheshwari et al. (2017) concluded that incorporating resiliency in design phase led to a reduction of up to 38% in the expected disruption cost of the BSC by optimizing depot locations (Maheshwari et al., 2017). Similarly, Soren and Shastri (2019) demonstrated that considering disruption (i.e., supply disruption in the form of drought) at the design stage can reduce the expected SC costs. They claimed this cost saving can be increased

even by increasing the disruption intensity. In this study, the saving amount was proposed as a penalty function on additional feedstock and shortfall. Figure 3.6 presents the frequency of risk factors. Therefore, incorporating such factors enables decision-makers to design a resilient bio-hub integrated network that operates efficiently in the face of disruptions. Although these results depend on the level and nature of disruptions and other parameters, the important finding is that presenting depots can increase BSC resilience if planned and designed meticulously.

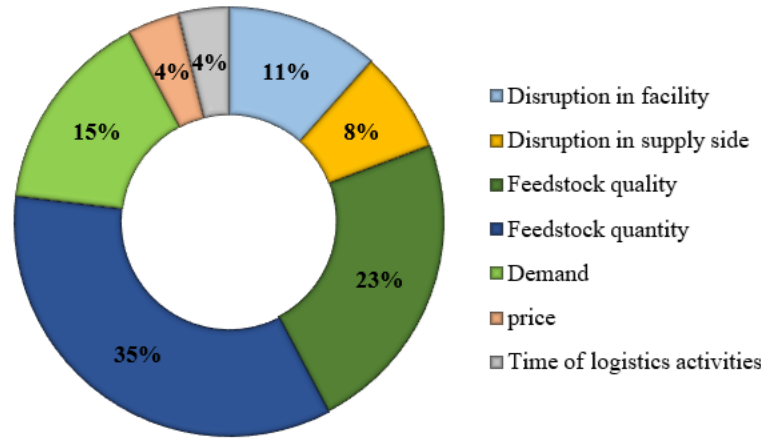


Figure 3.6. Frequency of risk factors

Findings illustrate that some studies developed integrated approaches to enhance the capabilities of applied mathematical modeling in finding optimal decisions using agricultural land management with numerical assessment criteria (ALMANAC) simulation, geographic information system (GIS), machine learning (ML), and MCDM. For example, ALMANAC simulation was employed to predict plant yield in different locations under climate changes (Aranguren et al., 2018). GIS, which can analyze geographical information, was used to determine feedstock supply and facility locations at high spatial resolution (He-Lambert et al., 2018; Ng et al., 2018). Goettsch et al. (2020) applied multiple ML methods in their study to decrease the number of potential depot locations given to the mathematical model and increase the quality of the solution. Furthermore, Gautam et al. (2022) implemented the analytic hierarchy process (AHP) along with mathematical programming separately to determine the location of terminals based on qualitative and quantitative criteria, respectively. Then, the authors employed benefit-cost analysis to incorporate the results of these two approaches. Data envelopment analysis also was used to assess the efficiency of potential alternatives and inject the selected ones into the mathematical programming model to choose the final locations (Babazadeh et al., 2017).

Regarding the solution method, solvers (e.g., CPLEX and Gurobi) have been mostly used to solve the mathematical models. When dealing with problems including non-linear terms, multiple decision variables, especially binary ones, and stochastic parameters, solving models using these solvers can pose significant challenges (Tiwari et al., 2021). To solve such complex and large-scale problems, different methods like decomposition-based algorithms (e.g., multicut L-shaped decomposition, branch and bound, and benders) and heuristic/metaheuristic algorithms (e.g., genetic algorithm, simulated annealing, ant colony, and tabu search) have been used to provide the solutions to mathematical programs.

3.4.2.2. Simulation

BSCs are subject to be influenced by multiple factors ranging from the seasonality of biomass availability to the intricacies of transportation logistics and storage (Mafakheri et al., 2021). Simulation is a powerful approach to analyzing such a complex and dynamic environment, enabling quantitative assessment of system behavior. This approach provides a flexible environment to model any relationship among actors and multiple variabilities, allowing for the incorporation of a high degree of complexity (Habibi et al., 2023a). Simulation is commonly employed to explore “what if” scenarios, offering valuable insights into a system’s performance over time (Katsaliaki et al., 2021). Indeed, this approach enables researchers to meticulously analyze network activities, facilitating efficient decision-making at both tactical and operational levels. Therefore, stakeholders can make informed decisions regarding various aspects of bio-hubs before initiating any investments. Findings show that this category comprises almost 10% of shortlisted papers, with a focus on resource utilization and biomass flow planning under certain bio-hub scenarios (see Table A2 in Appendix A). Moreover, the main sustainability aspect investigated in this category was the economic viability of the proposed bio-hub scenarios. These studies are further discussed as follows.

Using discrete event simulation (DES), Wolfsmayr et al. (2016) simulated the terminal processes to investigate the efficiency of adopting existing railway sidings to provide multimodal terminals for primary forest fuel transportation. They analyzed the daily and annual transshipment capacities and figured out bottlenecks in different terminal layouts under supply scenarios. Moreover, Väättäinen et al. (2017) examined the performance of a BSC with intermediate terminals at different distances. To this end, terminal-related factors such as location, investment cost,

transport method, truck utilization, and quality of terminal-stored feedstock were investigated. In a similar work, Fernandez-Lacruz et al. (2019) investigated the usefulness of terminals in supplying biomass to a combined heat and power plant (CHP) and biorefineries with varying sizes. They calculated the cost of feedstock handling in two scenarios, direct or combined via terminal transportation. Parameters such as machine efficiency, material flow, demand loss, and dry matter losses during storage were measured to compare these two scenarios. Using DES, Enström et al. (2021) studied the cost-efficiency of delivering feedstock to the port using intermediate terminals. The main aim of this study was to streamline logistics operations at the loading port for maritime transport of woody biomass. All these studies revealed that establishing such a terminal allows buffer inventory to manage uncertainty and facilitates the transportation of a high volume of biomass to other facilities (e.g., bioenergy plants).

The second simulation technique used in bio-hub implementation literature is system dynamics. This technique utilizes mathematical equations to represent the interactions and feedback loops within a system, providing insights into how changes in one part can affect the entire system (Nasiri et al., 2016). Using system dynamics modeling, Khoddami et al. (2021) explored two distinct coordination strategies, namely quantity discounts and cost-sharing in a hub-coordinated SC, to derive the optimal decisions for each actor of a BSC.

3.4.2.3. Multi-Criteria Decision-Making

MCDM methods are analytical approaches used when making choices involving multiple, often conflicting criteria. These methods assist in evaluating and comparing various alternatives by considering diverse qualitative and quantitative factors simultaneously. MCDM involves assessing options against a set of predefined criteria, assigning weights to these criteria based on their importance, and ultimately ranking or selecting the most suitable alternative. The goal is to provide a systematic and structured framework for decision-makers to navigate complex decision landscapes, ensuring a more informed decision-making process (Mottaghi et al., 2022). There are several MCDM techniques, such as the technique for order preference by similarity to ideal solutions (TOPSIS), decision-making trial and evaluation laboratory (DEMATEL), elimination and choice translating reality (ELECTRE), analytic network process, and AHP, which are different in terms of their characteristics (Kumar et al., 2017). However, within the literature of this category summarized in Table A2, content analysis reveals the utilization of AHP and TOPSIS. Given the

advantages of MCDM techniques in simultaneously analyzing different criteria and alternatives, location selection of bio-hubs has been mostly studied in these papers. Below, we further discuss these papers.

Kühmaier et al. (2014) defined a suitability index for potential terminal locations using AHP and fuzzy set theory. They integrated the stakeholder preferences and spatial constraints to calculate this index. Similarly, Lemire et al. (2019) applied AHP to weight location selection criteria of depots. How and Lam (2017) proposed an integrated approach using AHP and principal component analysis (PCA) to determine the location of processing hubs. In a recent study, which can be categorized in both MCDM and simulation models, Muerza et al. (2023) presented a decision support system for biomass procurement planning of IBLC. They used AHP for weighting the pre-determined criteria to be considered in the IBLC supplier selection problem and employed TOPSIS for ranking these suppliers. Then, to compare the economic and environmental feasibility of implementing IBLC with these suppliers, they integrated agent-based simulation and DES. They concluded that considering these centers increases the total profit by 55% while CO₂ equivalent emission is reduced by 24.2%.

3.4.2.4. Systematic Modeling

Apart from the strategic and tactical/operational decisions regarding bio-hubs discussed in the prior sub-sections, this subsection examines papers that scrutinize the technical aspects of operations within bio-hubs and the resultant performance of the network. Findings indicate that 27% of the shortlisted papers fall within this category, where techno-economic analysis (TEA) and life cycle assessment (LCA) techniques have been predominantly employed. However, a few other analyses using financial analysis, descriptive statistics, and ML methods have been conducted as well, which have been summarized in Table A3 in Appendix A. It should be mentioned that systematic modeling in these papers can include a variety of techniques such as TEA, LCA, financial analysis, structural analysis, regression analysis, descriptive statistics, software-based modeling, decision support system, input/output analysis, and statistical hypothesis testing (Jazinaninejad et al., 2022).

TEA is a methodological approach that assesses the economic feasibility and viability of a technological process (Lamers et al., 2015a). It involves the detailed examination of both the technical aspects and the economic factors associated with the development, implementation, and

operation of a technology or process. As such, incorporating technological considerations is crucial for a comprehensive assessment of the feasibility, efficiency, and sustainability of bio-hubs in addition to addressing the economic aspects (Lan et al., 2021). To this end, TEA has been implemented in some studies to compare the bio-hub concept with traditional systems and investigate the effect of preprocessing technologies that can be implemented within bio-hubs.

Muth et al. (2014) considered two logistics concepts: a traditional bale logistics system and an advanced supply system, including preprocessing biomass depots. Comparing the efficiency of these two systems, they concluded that the economies of scale enabled by the advanced supply system compensate for a considerable portion of the added logistics costs associated with additional depot transportation and processing activities. As a result, the final product incurs a slightly higher selling price compared to the traditional logistic system. Lamers et al. (2015a) analyzed three depot configurations to assess the economic viability of considering depots with different technical activities. They considered two standard depots with different technologies (i.e., conventional pelleting process and high-moisture pelleting process) and one quality depot with ammonia fiber expansion technology.

Similar to the previous study, they claimed that the benefits associated with depot facilities could outweigh the added costs. Patel et al. (2019) modeled different BSC models and investigated the technical and financial viability of switching from centralized to decentralized pyrolysis units (i.e., bio-hub). The decentralized pyrolysis system has the capability to adjust or modify its operations and processes in response to the specific conditions and environmental factors of different geographic regions and varying weather conditions. They finally concluded that utilizing a mobile pyrolysis system can reduce the costs of handling and transporting raw biomass, allow access to remote areas, and withstand adverse weather conditions. Additionally, when dealing with small-scale plants, they recommended implementing a decentralized system because of its portability and ability to reach remote areas. Liu and Bao (2019) suggested adopting the pre-treatment technology of dry acid in depots due to its advantages of zero wastewater generation. This technology leads to the higher collection of feedstock and consequently upscaling the biorefinery operations for bioproduct production. Recently, Lan et al. (2021) investigated the technological and economic aspects of distributed preprocessing systems within the context of fast pyrolysis biorefineries. They examined several SC configurations with various biomass blending

ratios and different biorefinery and preprocessing sites, as well as alternative preprocessing technologies.

LCA is a systematic way of evaluating the environmental impact of a product, process, or service from its extraction of raw materials to its disposal. (Vazifeh et al., 2023a). LCA considers resource use, emissions, and waste generation, providing a comprehensive analysis to guide more sustainable decision-making (de la Fuente et al., 2018; Sadaghiani et al., 2023). Using this approach, Nguyen et al. (2014) conducted a study to investigate the impact of the location and size of preprocessing depots on GHG emissions from agricultural residue logistics. To this end, they compared two location scenarios. In the first scenario, they considered equally distributed depots within the vicinity of counties that have access to high biomass supply density. In the second one, they determined locations with the shortest rail transport distance to the biorefinery while considering proximity to high-supply counties. Results showed the benefit of locating depots near direct railroad lines because this type of transportation has the lowest costs with better environmental performance. In another study, Dias (2014) assessed the environmental impact of roadside chipping of loose residues, terminal chipping of loose residues, and terminal chipping of bundled residues in fuel chip production. The main aim was to identify the SC configuration and machinery bringing the least environmental impact. They concluded that regardless of what equipment is used, roadside chipping of loose residues has less impact. While in terminal chipping configurations, it depends on the machinery type and distances travelled between the forest and the power plant. Regarding LCA of mobile production systems in pelletizing logging residues, de la Fuente et al. (2018) concluded that using the Swedish grid-based electricity mixes instead of stand-alone diesel-based electricity in the terminals has the potential to mitigate the environmental effects associated with this process. In another study, Kim et al. (2019) evaluated the environmental impacts of integrating a decentralized (depot-based) biorefinery with a coal-fired power plant. They demonstrated that utilizing biomethane and residual solids in the depot-based systems results in significantly lower biofuel selling prices compared to conventional centralized biorefineries. According to Lan et al. (2020), incorporating preprocessing depots reduces the energy consumption of biorefineries while increasing the overall life cycle energy and global warming potential. However, these findings are specific to their case study of blended feedstock (i.e., pine residues and switchgrass) utilization. The suggestion was made that environmental

impacts could be reduced by raising the proportion of switchgrass, given that energy consumption at the depot is primarily influenced by the higher moisture content of pine feedstock.

3.4.3. Case Studies in Bio-Hub Implementation

In addition to modeling approaches, the literature was analyzed in terms of their case study regions. The distribution of case studies on bio-hub implementation in the context of the BSC across different regions (i.e., 13 countries) reveals an interesting pattern providing valuable insights into the global landscape of this sustainable initiative. North America stands out with a substantial representation, comprising 61% of cases, of which 43 cases are in the USA and 11 cases in Canada (See Table 3.4). The higher concentration of bio-hub implementation case studies in the USA can be due to several factors, such as vast biomass resources and comparatively high annual production of forest and agricultural products. The diversity and abundance of biomass feedstock available across different regions of the country enhances the applicability and adaptability of these hubs (Nicholls et al., 2022). Moreover, the scale and diversity of the USA markets, in terms of both geographical distribution and industrial sectors, provide ample opportunities for bio-hub implementation. Different regions may have unique biomass resources and logistical challenges, prompting the exploration of diverse bio-hub models tailored to specific market demands. Moving to Europe, almost 16% of case studies have contributed to the literature, with six originating from Sweden and two from Finland. Similarly, in Asia, around 16% of case studies shed light on the bio-hub landscape, with China contributing seven cases. Although these studies have been customized to specific regions, considering the distinctive challenges and opportunities in bioenergy, their findings can be applied in other jurisdictions to highlight key considerations for successful bio-hub implementation. It is worth mentioning that having a suitable research infrastructure has played an important role in publishing studies in the indicated countries. However, the main aim is to apply insights earned from bio-hub incorporation across diverse regions and inform future research in areas with similar characteristics, facilitating knowledge transfer and stimulating creative thinking in this field.

Table 3.4. Frequency of case study region, biomass, and bioproduct types in the reviewed literature

Case Study	Frequency	Feedstock Type	Frequency	Bioproduct type	Frequency
North America	55	Agricultural Residues	43	Biofuel	54
Asia	15	Forest-based Biomass	42	Electricity (Power)	11
Europe	14	Energy Crops	17	Bioenergy	3
Not Specified	6	Livestock waste	4	Heat	4
		Municipal Waste	3	Bio-Chemicals	1
		Algae	2	Not Specified	20
		Not Specified	4		

These studies were analyzed based on the type of feedstock and the final bioproduct under investigation summarized in Table 3.4. The choice of feedstock may be influenced by some factors, such as regional factors (e.g., biomass yield and adaptability to different climate conditions and soil quality), economic factors (e.g., feedstock price and production cost), and the conversion rate to bioproduct (Mottaghi et al., 2022). According to this table, forest-based biomass and agricultural residues have been of special interest when bio-hubs are integrated within a BSC (i.e., 47% of papers). This may be due to their abundance and practical applications in BSCs. The utilization of energy crops is represented by 18% of studies, likely due to various influencing factors. Energy crops such as switchgrass often require dedicated cultivation efforts and might have associated challenges, such as land use considerations and potential competition with food crops (Zahraeet al., 2020). As such, researchers may be interested in initially exploring feedstock that is more readily available or has fewer associated complexities than energy crops. These statistics were followed by livestock waste with four cases, municipal waste with three cases, and algae with two cases, while the rest of papers did not explicitly mention the specific feedstock under examination. Moreover, Figure 3.7 illustrates that 70% of the papers investigated a single type of feedstock rather than multi-feedstock (i.e., 25%). However, given the total number of papers published each year, it appears that research on multi-feedstock studies is still emerging. Indeed, bio-hubs provide an opportunity to store a diverse array of feedstock types, each with varying availability throughout the year. These facilities can preprocess feedstock and produce uniform-format stable products, which enables effective management of potential supply disruptions arising from weather conditions and seasonal fluctuations in biomass availability (Hossain et al., 2024).

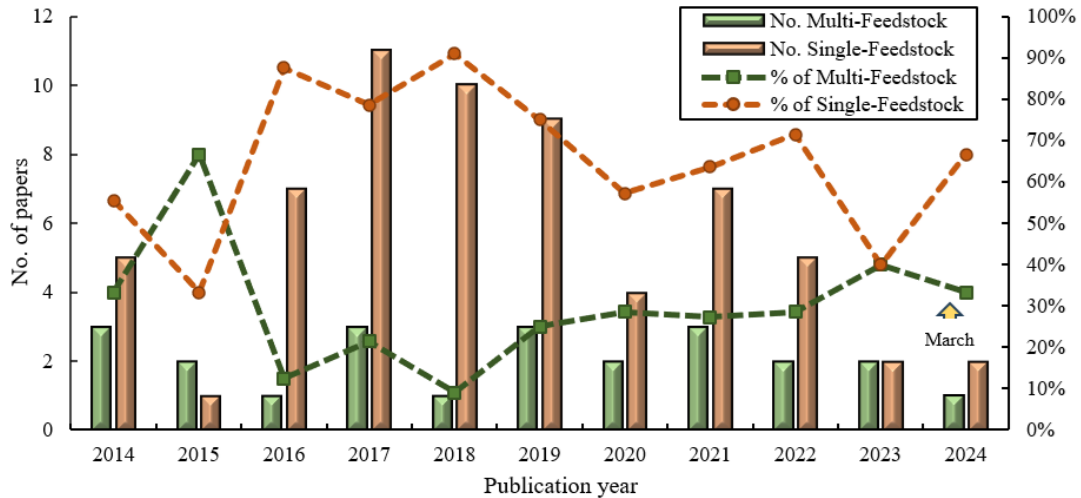


Figure 3.7. Distribution of published peer-reviewed journal papers dealing with single and multi-feedstock

Taking the final bioproduct into account, the studies were classified into biofuel (i.e., bioethanol, bio methanol, gasoline, biodiesel, biogas, and solid fuel like pellets), electricity (i.e., power), heat, and bio-chemicals. However, some studies have not distinctly specified the type of bioenergy, so the term "bioenergy" was employed to encompass these studies. Among the final products, the exploration of biofuel production is the center of academic research (i.e., 60%), while electricity and heat production have been less studied. Moreover, around 20% of the literature has not specified the bioproduct type. Approximately 90% of the case studies have concentrated on a single specified final bioproduct. This could be attributed to the complexity that arises in dealing with multiple feedstocks and end products, which leads to computationally time-consuming problem-solving on a large scale (Mottaghi et al., 2022). However, in Lan et al. (2020), Lan et al. (2021), and Gautam et al. (2022), authors have investigated the possibility of producing different bioproducts using multi-feedstock sources.

3.5. Policy Aspects and Government Programs

Up to this point, the focus of the review has been primarily on academic studies published in peer-reviewed journals. However, it is essential to acknowledge the existence of valuable research originating from government programs and national laboratories concerning bio-hubs and their operations. These studies illustrate the engagement and support of several countries in advancing bio-hub projects. To ensure a comprehensive literature review and gain insights from policymakers' perspectives, this section discusses the technical reports published by government agencies.

A noteworthy example is the Finnish-Swedish project (Finnish-Swedish project, 2019), which was dedicated to the development of a bio-hub model. This project assessed the business and operational structure of forest biomass terminals, aiming to improve their ability to serve conventional forest sectors and emerging biorefining industries. According to the results of this work, the created bio-hub model, which was adopted by the Bastuträsk terminal in Northern Sweden, could provide practical information on business plans for terminal entrepreneurs. Moreover, this model could offer insights into i) assessing raw material availability and selecting an appropriate terminal location, ii) designing terminals and improving operational efficiency, and iii) raw material treatment strategies in terminals. The researchers transformed the bio-hub model into a web-based tool to assist stakeholders in making informed decisions.

Furthermore, under IEA bioenergy Task 43, several projects on bio-hub have been conducted around the globe with the aim of quantifying the value of bio-hubs. In a collaborative project conducted by IEA and Natural Resources Canada in 2020, a SWOT analysis was done to understand strengths, weaknesses, opportunities, and threats for existing or potential bio-hubs in Canada. In this project, stakeholders and partners from across Canada were asked to investigate strategies for successfully establishing and implementing bio-hubs in different regions to enhance the Canadian bioeconomy. According to the results published in their report (Nasso et al., 2020), the availability of sustainable biomass, maintaining the quality and quantity of feedstock and access to a highly skilled workforce were identified as the main strengths in the biomass sector in Canada that could help promote bio-hub projects. They identified the potential opportunities afforded by bio-hub implementation to use underutilized feedstock and engage non-traditional players in bio-based projects. However, they concluded that the limited access to capital investment and the complexity of intergovernmental structures and priorities may hinder bio-hub implementation in Canada. Furthermore, various sources of uncertainty, such as weather conditions, policy support, and market fluctuations, as well as a lack of trust stemming from past failures in bio-economy projects, could pose significant threats to bio-hub implementation initiatives.

Another research project was conducted in Australia (IEA Bioenergy Task 43) to examine the viability of bio-hubs in Southeast Queensland, Australia. The study analyzed the availability of biomass in private native forests and assessed the viability of establishing bio-hubs at both local and regional levels to produce value-added products. Additionally, an economic analysis of two

proposed bio-hub scenarios was conducted: one aimed at biochar production, and the other focused on pellet production. The analysis considered factors such as biomass resources, supply chain costs, and regional market dynamics to determine the financial and operational feasibility of the bio-hubs (Berry, 2022).

In another project under Task 43, Pradhan et al. (2022) conducted a TEA of producing several bioproducts in bio-hubs at certain locations in western, central, and eastern Canada. They studied different pathways of producing forest-based bioproducts within Canadian bio-hubs in terms of their economic feasibility. More recently, Rai and Monaghan (2024) analyzed the environmental sustainability of bio-hubs in Ireland using LCA. In their report, they investigated three sample bio-hub scenarios: i) A bio-hub that converts post-harvest agricultural residues in Croatia to solid fuel pellets used in distant domestic heating, ii) A bio-hub that converts forest residue in Ireland to gaseous biofuel to power an Irish timber truck fleet, and iii) A bio-hub that converts forest residue, also in Ireland, to crude bio-oil, which is then transported to an oil refinery to produce lower-carbon diesel. They calculated GHG reductions of 90% for the first and second bio-hubs and 62% for the third one.

In addition to the IEA, the Bioenergy Feedstock Library of the US published a report to provide a survey of the publicly available analytical data about the biomass feedstock types and different equipment used for feedstock preprocessing in the US. In this report, researchers discussed the importance of preprocessing operations in successfully implementing bioenergy projects, particularly at large-scale production levels (Emerson et al., 2023). The Idaho National Laboratory asserted that feedstock preprocessing in depots for densification can reduce moisture content through a drying process, consequently lowering associated storage and transportation costs (Jacobson et al., 2014).

3.6. Discussions and Future Research Directions

Reviewing the literature, including scientific papers and technical reports revealed that the developing bioeconomy is in need of adopting practical strategies to make residues and by-products available in accessible locations and at lower costs (Hossain et al., 2024). Incorporating bio-hubs within networks offers an opportunity to reduce the risk of feedstock shortage, facilitate transportation activities, benefit from economies of scale, and consequently reduce the total cost of the network (Aboytes-Ojeda et al., 2021). As the literature illustrated, scholars have tried to

focus on investigating certain aspects of bio-hubs that can contribute to making them a viable and sustainable solution in practice. Although some important aspects have been studied, there are still critical gaps that necessitate further exploration in this area. This section presents and discusses potential research directions from BSC and modeling perspectives.

3.6.1. Analyzing Findings from the BSC Perspective

As indicated by the results, the selected papers have predominantly concentrated on the strategic decision of bio-hub design, mainly location selection along with biomass flow planning (i.e., 72%), and in some cases (i.e., 22%), capacity planning of bio-hubs (see Figure 3.8). However, these strategic decisions might be impractical or infeasible at tactical and operational levels (Akhtari and Sowlati, 2020). For instance, when biomass flow is planned at the strategic or tactical level, the quantity of biomass transshipped to (from) bio-hubs might not be enough to meet the daily demand of the other facilities (Akhtari et al., 2018). To prevent such problems, future studies can aim at developing integrated models to ensure the feasibility of establishing bio-hubs while addressing operational level variabilities, such as demand and lead time (Jazinaninejad et al., 2022).

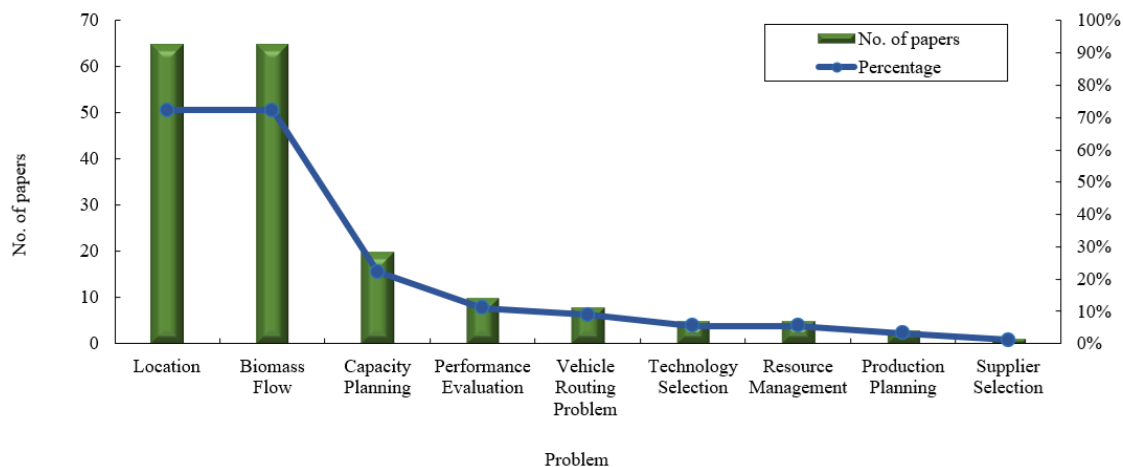


Figure 3.8. The problems studied in the literature of bio-hub implementation in BSCs

Furthermore, the findings from our review revealed that the technical aspects of bio-hubs have not been sufficiently studied. According to Tables A1 to A3, bio-hubs were mostly considered as an intermediary point to facilitate storage and logistical activities. However, as depicted in Figure 3.2, various pathways can be pursued to produce multiple products for further processing or end-uses, depending on the type of feedstock available (Pradhan et al., 2022). Different regions may have

varying availability and suitability of biomass resources, ranging from agricultural residues and energy crops to forestry residues (Mottaghi et al., 2022). By leveraging this diversity and decreasing the reliance on a single feedstock, bio-hubs introduce an interesting avenue for investigating the use of multiple sources of feedstock to produce different outputs such as power (i.e., electricity), heat, biofuel, bio-chemicals, and biomaterials (Nasso et al., 2021). Razm et al. (2023) demonstrated the potential of utilizing multi-feedstock to diversify the product range of biorefineries, allowing them to match energy demand fluctuations. Although their BSC initially focused on electricity generation, storage limitations prompted the consideration of simultaneous biofuel and electricity production. In this work, biofuel was supposed to be stored for subsequent conversion into bioenergy. Therefore, by increasing the availability of a uniform-format stable feedstock, the resilience of BSCs against seasonal variations and weather fluctuations can be increased (Kulišić et al., 2019; Lan et al., 2021; Hossain et al., 2024). In this scenario, optimizing production planning (Muerza et al., 2023), technology selection (Liu and Bao, 2019; Patel et al., 2019), and resource management (Fernandez-Lacruz et al., 2019; Enström et al., 2021) within bio-hubs becomes imperative. Additionally, future research can examine the optimization of bio-hub ordering practices to ensure the timely fulfilment of biorefinery demands (Nguyen and Chen, 2022). Such decisions could enhance the overall effectiveness and adaptability of BSCs, leading to improved operational performance and sustainability (Jazinaninejad et al., 2022).

The literature review also highlighted the importance of biomass quality in the context of the BSC as feedstock. In particular, agricultural and forest residues exhibit high-quality variability (Sokhansanj et al., 2006). The quality, which is defined by moisture and ash contents, can have a significant impact on the design and management of the BSCs (Aboytes-Ojeda et al., 2022a). Considering biomass quality and associated cost parameters can lead to different BSC topologies (e.g., location and number of facilities) and transportation paths (Castillo-Villar et al., 2017). Moreover, biomass is considered a unique perishable product undergoing continuous degradation and is unlike other perishable products that have predetermined shelf lives. Indeed, the deterioration of biomass depends on several factors (e.g., storage and preprocessing methods, type of feedstock, and moisture content). As such, biomass yield decreases over time as a result of ageing of feedstock in storage (Razm et al., 2023). Despite its crucial significance, most studies have overlooked this characteristic of biomass in decision-making processes to simplify their proposed models. Therefore, it is vital to explore the variability in feedstock quality and

degradation rate when making strategic and tactical/operational decisions regarding bio-hubs. Furthermore, it was revealed that different sources of uncertainty (e.g., policy support, market fluctuation, and technical errors) and disruption risks (e.g., natural disasters and impact) pose significant threats to the successful implementation of bio-hub projects (Liu et al., 2017; Abasian et al., 2019). Such failures can reduce investors' confidence and deter similar projects from being launched (Nasso et al., 2020). Therefore, future studies are needed to explore ways of designing resilient bio-hubs while considering potential uncertainty factors.

The content analysis illustrated that most of the BSC networks proposed by scholars are either centralized or decentralized. Centralized networks may suffer from bottlenecks and delays due to reliance on a single decision-making point. While decentralized networks may struggle with coordination and consistency issues across multiple nodes as well as high operational costs (Ahlqvist et al., 2022). In practice, each actor seeks to optimize their individual outcomes, which may potentially conflict with the objectives of others (Mafakheri et al., 2021). For example, bio-hubs aim to minimize their total cost, while suppliers seek to maximize their profits from selling feedstock to these hubs. According to IEA, one of the potential challenges in fostering bio-hub implementation is the lack of frameworks to incentivize end-users to use more bioproducts and motivate stakeholders to invest in bio-based industries (Kulišić et al., 2019; Nasso et al., 2020). To address all these challenges, coordination mechanisms such as quantity discount, risk sharing, cost sharing, and profit sharing can be implemented to create a trade-off between the objectives of individual actors and improve the performance of the whole BSCs.

To ensure that bioenergy serves as a sustainable alternative to fossil fuels, comprehensive assessments of economic, environmental, and social aspects (i.e., sustainability pillars) become crucial, especially when introducing new facilities (e.g., bio-hubs), technologies, or equipment into a BSC (Jazinaninejad et al., 2022; Mottaghi et al., 2022). As Figure 3.9 demonstrates, the most studied sustainability pillar regarding bio-hub scenarios was the economic aspect (e.g., investment, transportation, inventory, and preprocessing costs), studied in 76% of the papers. However, environmental and social effects of bio-hub incorporation have been examined in only a few studies, despite their significance (see Figure 3.9). Operating these facilities can result in large-scale production of biomass, collection, transportation, and adoption of preprocessing conversion technologies, leading to environmental impacts (Lan et al., 2020; Toba et al., 2023; Rai and Monaghan, 2024). While bio-hub implementation can stimulate the local economy and social

indicators by creating jobs in transportation, operation, and construction sections, environmental indicators like land use, soil quality, and water utilization may pose challenges (Nicholls et al., 2022). Therefore, future endeavors should focus on developing multi-objective models to navigate trade-offs among the three sustainability pillars.

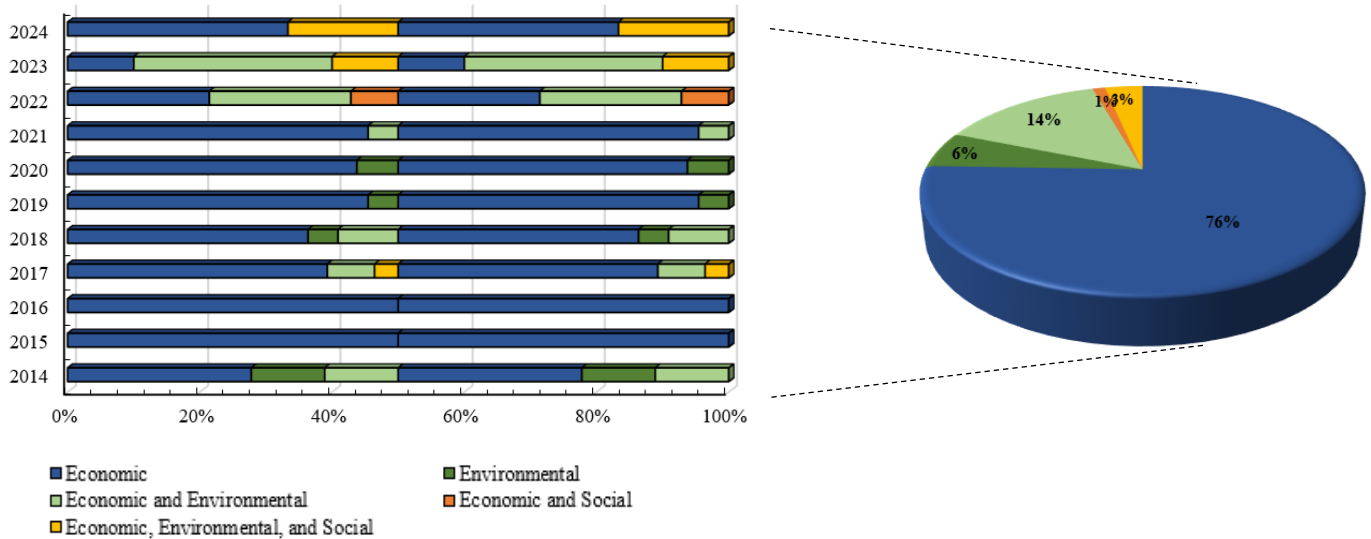


Figure 3.9. Sustainability pillars of bio-hub implementation in BSCs

3.6.2. Analyzing Findings from the Modeling Perspective

Given the modeling approaches, the results of the analyses demonstrated the widespread application of mathematical programming in addressing bio-hub implementation challenges within BSCs. This can be attributed to its ability to provide optimal decisions for bio-hub designing and planning. However, there are key areas that warrant further exploration. In terms of modeling uncertainties, literature predominantly adopts a two-stage stochastic modeling approach, which proposes a known probability distribution for uncertain parameters. Decomposition-based methods and heuristic and metaheuristic algorithms have been employed in literature to solve these problems. However, as the number of uncertain parameters increases, the computational complexity increases significantly (Mavromatidis et al., 2018). Approaches like robust optimization and relatively newer ones, such as ML and simulation techniques, offer promising directions for exploration, especially in scenarios where there is limited and imprecise parameter information (Habibi et al., 2023a). Robust optimization proves valuable in addressing uncertain

parameters when their probability distribution function is either unknown or challenging to estimate. The solution of this approach is more reliable and less vulnerable to variations because it considers worst-case scenarios (Behzadi et al., 2017; Kalhor et al., 2023). Leveraging the learning and predictive capabilities of ML approaches allows for their integration with other methods (e.g., mathematical programming) to formulate data-driven approaches (Habibi et al., 2023a). Keith et al. (2024) illustrated that ML algorithms (e.g., decision tree, random forest, logistic regression, k-nearest neighbors, and support vector machine) can reduce the computational expensiveness of stochastic programming models and consequently reduce the complexity of these problems. Furthermore, simulation techniques offer insights into the dynamism and uncertainty of operational factors by analyzing interactions among agents. In addition, these techniques can model the impact of external stressors and influencing factors (such as climate conditions, policies, incentives, state of economy, and competition) on the day-to-day operation of a BSC (Groundstroem and Juhola, 2021). As such, implementing such approaches not only enhances the model's capability to handle uncertainty but also facilitates making well-informed decisions that align with real-world scenarios.

In addition to the mentioned directions, government policies can play an important role in scaling up bioenergy production and facilitating bio-hub implementation. Supportive policies have the potential to stimulate and boost investments in bioenergy projects by providing financial incentives, tax credits, or subsidies to such enterprises (Vazifeh et al., 2023b). Consequently, the creation of new demand markets for biomass feedstock and bioenergy is encouraged, fostering the establishment and expansion of bio-hubs. Therefore, there is a need for a quantitative analysis of the impacts of policies and regulations on bio-hub implementation. In this regard, system dynamics simulation can offer a macro-level analysis for decision-makers. Furthermore, methods like game theory can assess the strategic interactions between policymakers and other stakeholders, aiding in the identification of policies that lead to mutually beneficial outcomes and effectively coordinating an entire BSC (Vazifeh et al., 2023c).

3.7. Conclusions

Literature review in the context of BSCs demonstrates that decision-making processes of preprocessing and storage facilities, such as bio-hubs, have attracted less attention compared to other players' problems (e.g., suppliers and conversion facilities). Although this trend shows a

positive development, there is still much room for improvement. Recognizing the significance of bio-hubs in BSCs underscores the critical need to delve deeper into this aspect. They enable better resource utilization, promote circular economy principles, and reduce the environmental footprint associated with biomass logistics. Hence, these hubs could contribute to the overall resilience of the BSCs and ensure a more sustainable and cost-efficient approach to bioenergy production.

This literature review aimed to address the existing research gap by exploring the multifaceted aspects of bio-hubs, as well as the advantages, challenges, and opportunities associated with their implementation. Following the five-step guideline proposed by Denyer and Tranfield (2009) for SLR resulted in the identification of 90 relevant papers published within the last ten years. A meticulous analysis and categorization of these studies was conducted to explore their limitations and offer potential research directions. The findings revealed a predominant focus among researchers on the design of bio-hubs, particularly in determining their optimal locations using mathematical programming models. Given that biomass supply and bioproduct demand areas are typically not located close to each other, determining the strategic location of bio-hubs is critical. Although the selected papers give valuable insight into the problem under investigation, some important aspects have been given limited focus or have been overlooked.

It is recommended to investigate tactical and operational level decisions, such as resource management, inventory, and production planning within bio-hubs along with strategic decisions. Furthermore, to accurately capture the dynamic and uncertain nature of the BSC, it is essential to integrate various sources of uncertainty and account for biomass degradation in the decision-making process. Additionally, examining the impact of coordination strategies and government policies on the performance of bio-hubs and BSCs presents a compelling avenue for future research. Consideration of environmental and social aspects in the implementation of bio-hubs, coupled with economic criteria, is also recommended to enhance the competitive advantages of bioproducts. From the modeling viewpoint, powerful approaches, like ML and simulation models, can be applied either individually or in combination to address such complex and dynamic problems. It is worth mentioning that the present study concentrated on quantitative approaches for analyzing bio-hub implementation within BSCs, excluding empirical studies. As such, prospective researchers are encouraged to explore qualitative techniques, such as questionnaire-based or interview-driven empirical studies, to capture subjective experiences and stakeholder perspectives in this field.

Chapter 4: Resilience Analysis of Biomass Supply Chains under Disruption Propagation and Recovery Strategies: An Agent-based Approach

4.1. Introduction

The increasing concerns on energy security and climate change, have given rise to the energy transition agenda aiming at diversifying the energy sources and moving towards renewable energies (Kheybari et al., 2023). This transition is perceived as promoting eco-friendly and sustainable power generation alternatives to ameliorate environmental impacts while meeting the ever-growing global energy demand (Umar et al., 2023). Among renewable energy resources, biomass has emerged as an attractive option due to (i) abundant and wide range of feedstock (e.g., agricultural residues, forestry residues, and energy crops), (ii) versatility in applications (e.g., solid and liquid fuel, electricity, and heat), and (iii) ability to utilize waste materials, thereby offering a sustainable solution for both energy production and waste management (Jazinaninejad et al., 2022). Moreover, biomass facilities have higher energy conversion and loading factors as well as lower levelized capital and operating costs in comparison with solar and wind energy technologies (Mafakheri et al., 2021). Accordingly, the transformation of biomass into bioenergy has attracted significant interest among academics and industries as a renewable, abundant, and affordable energy alternative.

Despite the several advantages offered by this renewable energy resource, its supply chain (SC) introduces unique complexities (Vazifeh et al., 2023a). Biomass sourcing relies on natural resources, which are subject to variability based on geographical location and seasonal changes. Weather fluctuations not only influence biomass availability but also directly impact energy demand. For instance, increased demand for heat in domestic households during cold weather periods can deplete inventories rapidly, leading to sudden shortages in feedstock (Esmaeili et al., 2023). Additionally, biomass processing and conversion activities involve complex operations and technologies, increasing the likelihood of equipment failures or technical issues (Galik et al., 2021). Moreover, biomass distribution activities often face logistical limitations and require extensive transportation networks, which results in transportation delays. All these challenges make the biomass supply chain (BSC) more vulnerable to disruptions in comparison with other conventional

SCs (Mohammadi et al., 2023). Therefore, planning the whole BSC introduces a high level of complexity due to the various sources of risks and operational interrelationships among the BSC stakeholders.

Disruptions can significantly impact the smooth flow of goods and services within supply chain networks (SCNs), leading to delays, increased costs, loss of productivity, and customer dissatisfaction (Karakatsoulis and Skouri, 2023). In response, organizations should adopt risk management practices (see Figure 4.1) involving the identification, assessment, and mitigation of potential risks that could affect the performance of SCNs (Pournader et al., 2020). According to the literature, a broad range of practices have been suggested to fortify supply chain resilience (SCR) and mitigate the disruptions' effects, known as resilience strategies (Faruquee et al., 2024). Although there is growing attention toward SCR, a major part of the studies is devoted to theoretical implications or has encountered challenges in accurately quantifying the multifaceted nature of disruptions. In fact, the reliability of SCR quantification metrics and frameworks remains questionable, highlighting the need for more robust ones to provide accurate insights into the system's condition. These measurements are essential for understanding the ability of SCNs to withstand and adapt to disruptions while enhancing ongoing operational efficiency and flexibility in a dynamic environment (Aldrighetti et al., 2021). This gap is particularly evident within BSCs, which are highly vulnerable to several disruptions (Valipour et al., 2024).

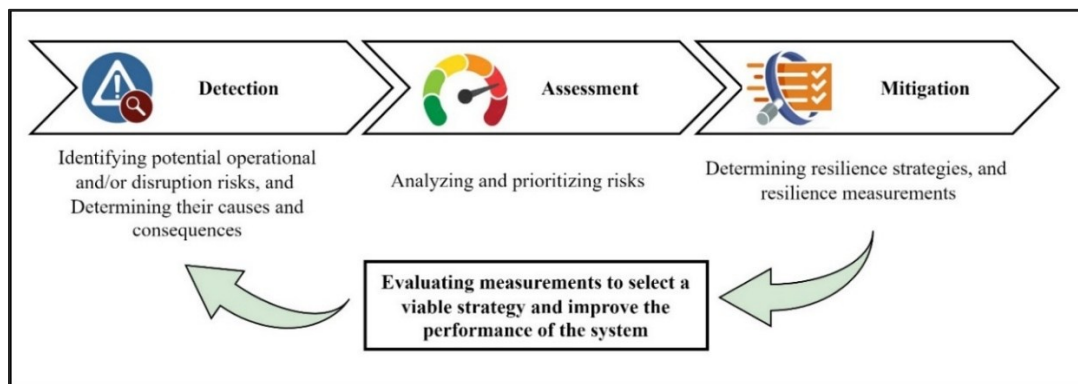


Figure 4.1. SC risk management practice

Accordingly, the current study seeks to address three main research questions:

- (i) How can risk-based attributes, such as resiliency, be quantified?
- (ii) How do mitigation strategies alleviate the disruption effects?
- (iii) How can dynamism and interdependence among entities and short-term vulnerabilities be effectively incorporated in SCR analyses?

The main aim of this study is to develop a robust framework for systematically quantifying SCR under resilience strategies, with a focus on analyzing disruption propagation throughout SCN. This framework is supported by an agent-based simulation (ABS) model to provide practical implications and assist decision-makers (DMs) in adopting viable solutions. This modeling technique excels in handling non-linearities and temporal dynamics of systems (Taghizadeh et al., 2021). When a disruption occurs, SC entities do not react in a uniform, deterministic manner. ABS allows for the modeling of these diverse responses, capturing emergent phenomena like ripple effects, cascade failures, and recovery patterns, which are often missed by other modeling techniques (Habibi et al., 2023a). Following defining agents and modeling behavioral rules of the proposed BSC, uncertainty sources are systematically fed into the model through probability distributions to facilitate a robust representation of stochasticity within the network. Subsequently, several mitigation strategies are integrated into the model design to enhance resilience. These strategies are paired with disruption scenario settings, including inputs like the number of nodes or links disrupted, the intensity of each disruption, and the duration of these disruptions for each affected node. To reflect time-dependent behavior and uncover hidden vulnerabilities, a dynamic disruption and recovery threshold is defined to activate and terminate recovery strategies instead of considering predetermined static time periods. After simulating scenarios over a specified planning horizon, the observed outcomes are passed to the resilience measurements to characterize overall SCR. In this stage, a comprehensive set of resilience metrics, including six unique indicators of reliability, preparedness, responsiveness, persistence, resourcefulness, and recovery time are adopted. These indicators are quantified using structural metrics derived from the key network characteristics of density, criticality, and connectivity. Each of these indicators is measured during pre-disaster, disaster, and post-disaster periods to capture the ripple effect of the disruptions and illustrate the behavior of the re-designed network. To demonstrate the applicability of the proposed framework in addressing real-world problems, three Quebec northernmost Inuit communities are evaluated as the case study.

The remainder of this study is organized as follows: Section 4.2 explains additional aspects of ABS, followed by the case study in Section 4.3 and a detailed description of the proposed approach in Section 4.4. Section 4.5 discusses key findings of the proposed framework and practical implications. Finally, the concluding remarks and future research directions are presented in Section 4.6.

4.2. Methodology

In today's intricate landscape of supply chain management, characterized by abundant uncertainties and inevitable disruptions, the utilization of modern analytical tools to make well-informed decisions has become indispensable (do Amaral et al., 2022). Simulation is one of the most powerful and popular techniques for modeling complex systems replicating a real system using a computational model (Abdelmegid et al., 2023). The literature demonstrated the utilization of four main types of simulation to model SCs, including Monte Carlo, SD, DES, and ABS. Monte Carlo and SD employ mathematical equations to construct their simulation models, whereas DES and ABS rely on the implementation of computer codes alongside heuristics (Goodarzian et al., 2024; Saisridhar et al., 2024). DES works well with systems that have clearly defined processes and events since its main focus is on simulating the flow of entities through a system and the discrete events that affect their movement (Paulo et al., 2022). ABS, on the other hand, places more emphasis on the actions and interactions of autonomous agents inside the system, making it powerful in capturing the complexities of systems with external stressors and multiple sources of uncertainties (Habibi et al., 2023a). Both methodologies have their strengths and applications, and the choice between them depends on the specific characteristics of the system under study and the research objectives at hand.

ABS which is the main approach of this study, is a method to simulate systems using agents characterized by numerous attributes such as individuality, autonomy, and ability to negotiate and interact. As such, agent-based modeling can be considered a bottom-up approach, whereby the overall behavior or objective of the system is defined by aggregating the simultaneous behaviors or objectives of its components (Saisridhar et al., 2024). Generally, this model comprises three main components: agents, agent relationships, and environment (Seçkiner and Koç, 2022; Anylogic Help, 2024). Agents represent autonomous entities with defined attributes and behaviors, capable of interacting with each other and responding to changes in their environment based on

the defined rules. In this model, agents can represent a wide range of entities, (e.g., products, equipment units, vehicles, and organizations) in various roles. Figure 4.2 depicts the visual representation of a general ABS model, illustrating its mechanism of transforming any segment of the SC into an individual module (Sun et al., 2022).

As depicted in the figure, each participant in the SC is treated as a module accessible through the central agent. Within each module (e.g., factory), diverse tasks (e.g., procurement, inventory management, production, sales, and transportation) can be executed based on the module's primary role and predefined rules (e.g., ordering mechanisms, inventory policies, and production procedures). The main focus of the ABS is on the individual entities of a system, rather than both the process-oriented DES and a highly abstract SD approach (Seçkiner and Koç, 2022). Specifically, the growing emphasis on studying SCR has underscored the significance of agent-based modeling, particularly in domains such as BSC that involve numerous components and sources of disruption and operational risks (Aalto et al., 2019).

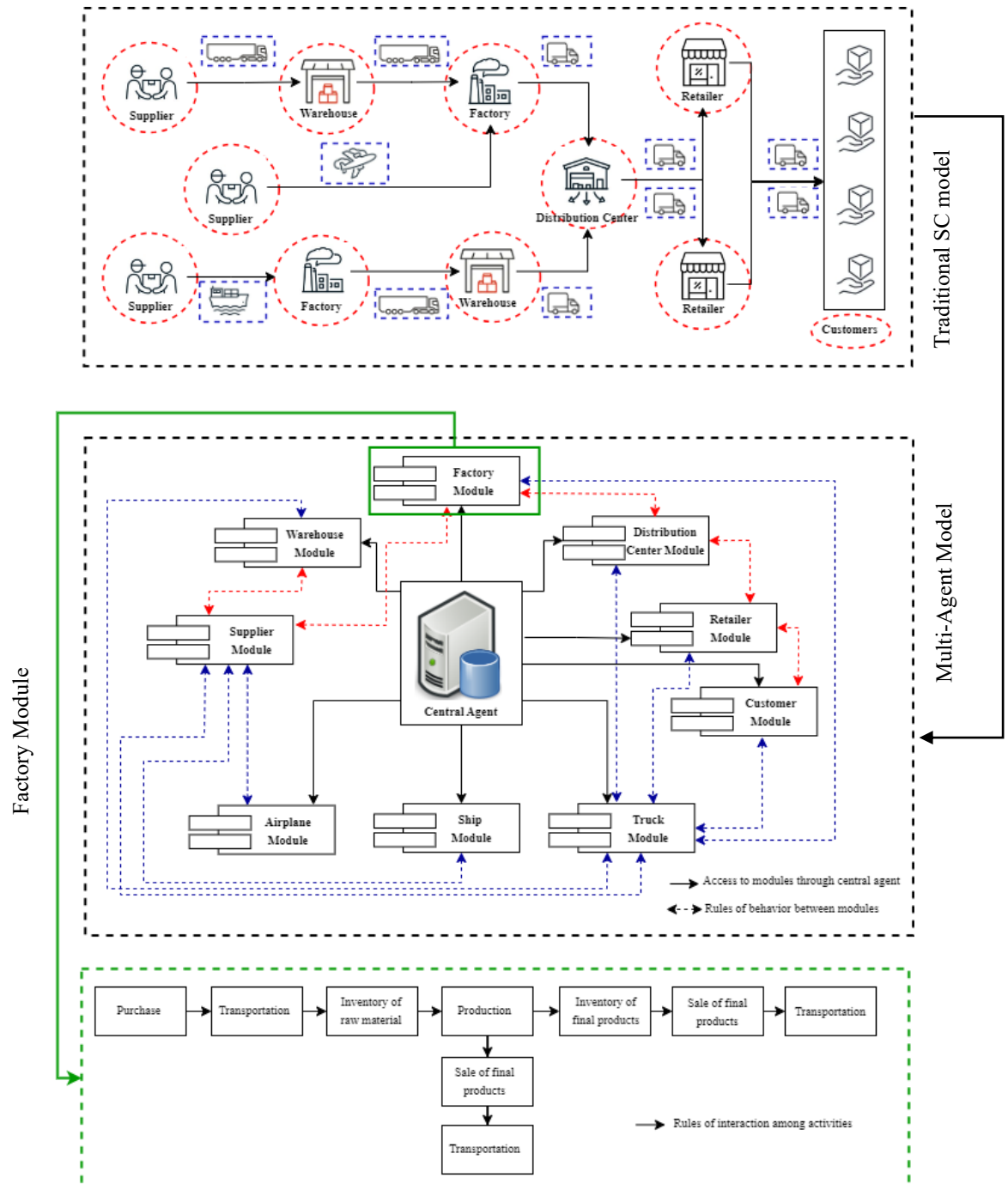


Figure 4.2. The multi-agent-based representation of a SC

4.3. Case Description

To deal with challenges associated with BSCs some studies have recently introduced the relatively new SC concept under various terms (e.g., hub, depot, terminal, and yard) which can collectively be referred to as bio-hub (Valipour et al., 2024). These facilities serve as intermediary locations between suppliers (e.g., forests) and end users (e.g., biorefineries), where raw materials are processed to meet the necessary quality standards and stored to deal with supply and demand fluctuations (Gautam et al., 2017). Furthermore, bio-hubs act as central points for multimodal transportation activities, streamlining the collection and processing of feedstocks (Enström et al., 2021; Vazifeh et al., 2023b). Bundling of supply quantities and creating distribution terminals/hubs has been suggested and implemented across various sectors such as manufacturing, agriculture, and services. However, regarding BSCs, there remains a necessity to establish such hubs worldwide, especially in regions characterized by extensive geography and where numerous remote communities exist (Mafakheri et al., 2021). The target of the proposed study is planning a resilient BSC integrating bio-hubs in three Quebec northernmost Inuit communities of Kangigsujuaq (KA), Salluit (SA), and Ivujivik (IV) in Nunavik region (see Figure 4.3). The unique geographical positioning of these communities presents a distinctive logistical challenge, as their sole access is through waterways (i.e., Hudson Bay, and Labrador Sea). Like other remote communities in Canada, these communities, which are off grid as well, rely on diesel as their primary source of electricity to meet their energy needs.



Figure 4.3. Northern communities in Quebec and their locations

Therefore, the proposed BSC has three main participants: suppliers, bio-hubs, and remote communities with local storage capacities. Since feedstock is supplied from distant small-scale suppliers and waterways are not available all year round, aggregating the needs of communities at bio-hubs can increase the supply scale and streamline ordering processes. As such, two bio-hubs are prepositioned in the network, each representing an individual pathway. Each bio-hub is expected to be supplied by participant suppliers selected based on associated capacity, price, and distance. Moreover, bio-hubs act as intermediary points for communities to meet their demand, considering their geographical dispersion and distance. In this network, communities are responsible for electricity generation from biomass as well as storing feedstock in local storage facilities, which help meet short-term needs. However, there is a possibility of switching to an alternative fuel (i.e. diesel) in case of feedstock shortage to avoid electricity outage. Although bio-hubs offer the potential to enhance the efficiency of the BSC, disruptions such as extreme weather events, crop failures, transportation delays, or equipment breakdowns may severely impact the reliability and continuity of bio-hub implementation. Therefore, any failure in bio-hub operations can significantly affect bioenergy generation in downstream echelons. Given the criticality of these facilities, recovery strategies are implemented to mitigate the effects of potential disruptions on bio-hub's performance.

4.4. Proposed BSC Network Simulation

The proposed network is modeled in three phases, starting with a conceptual analysis to understand the processes within the SC. Once the necessary data is collected, agents and their behaviors are modeled. Figure 4.4 presents an overview of the ABS model steps and modules, while Table 4.1 outlines all required inputs and expected outputs for the ABS setup. This model has been developed in AnyLogic 8.8.1 Personal Learning edition. Figure 4.5 provides a detailed representation of the AnyLogic modules for the proposed BSC, along with their key components such as inputs, variables, events, collections, and functions. Agents are built through an object-oriented approach, and actions are specified through the defining the specific rules of interactions. To address the dispersed geographical distribution of biomass resources, the geographic information system (GIS) has been chosen as the environment for the BSC simulation model. Within this environment, precise geographical distances can be determined between any two agents, facilitating the identification of the shortest route between them.

In simulation models, unlike traditional optimization models where the structure and formulation can be explicitly presented, much of the model's logic is embedded in code. In this study, all actions were executed using Java-based scripting within the AnyLogic environment. Representing interactions of agents and decision-making processes in ABS is challenging, as they are driven by behavioral algorithms rather than mathematical equations. To enhance clarity and provide insights into the agents' overview and their behaviors, Subsection 4-5-1 elaborates on the key algorithms governing their operations. Following the BSC simulation, Subsection 4-5-2 outlines the disruption scenarios and resilience strategies. Subsequently, Subsection 4-5-3 explains the resilience measurements utilized to quantify the SCR.

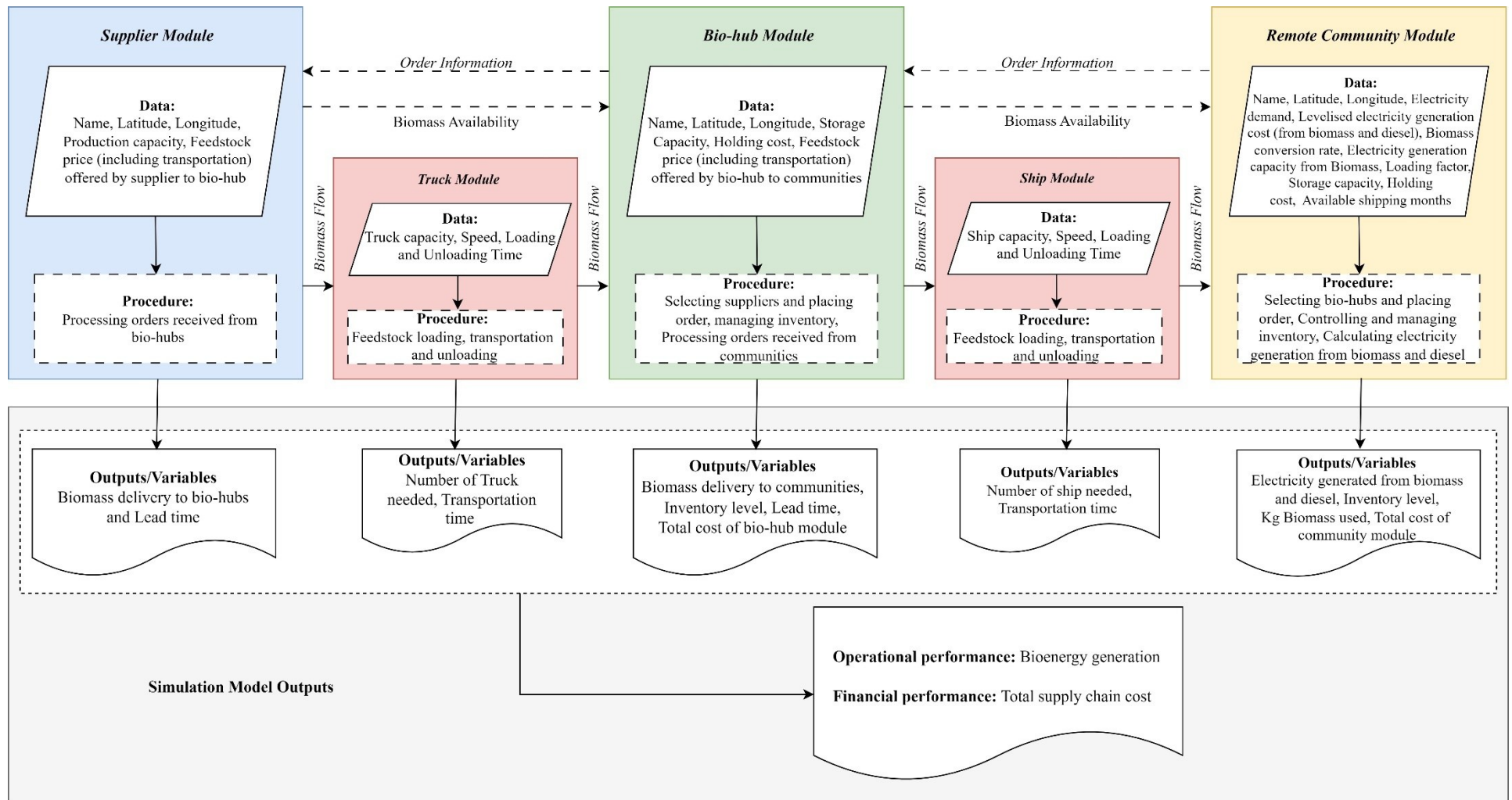


Figure 4.4. The proposed ABS model of the case study

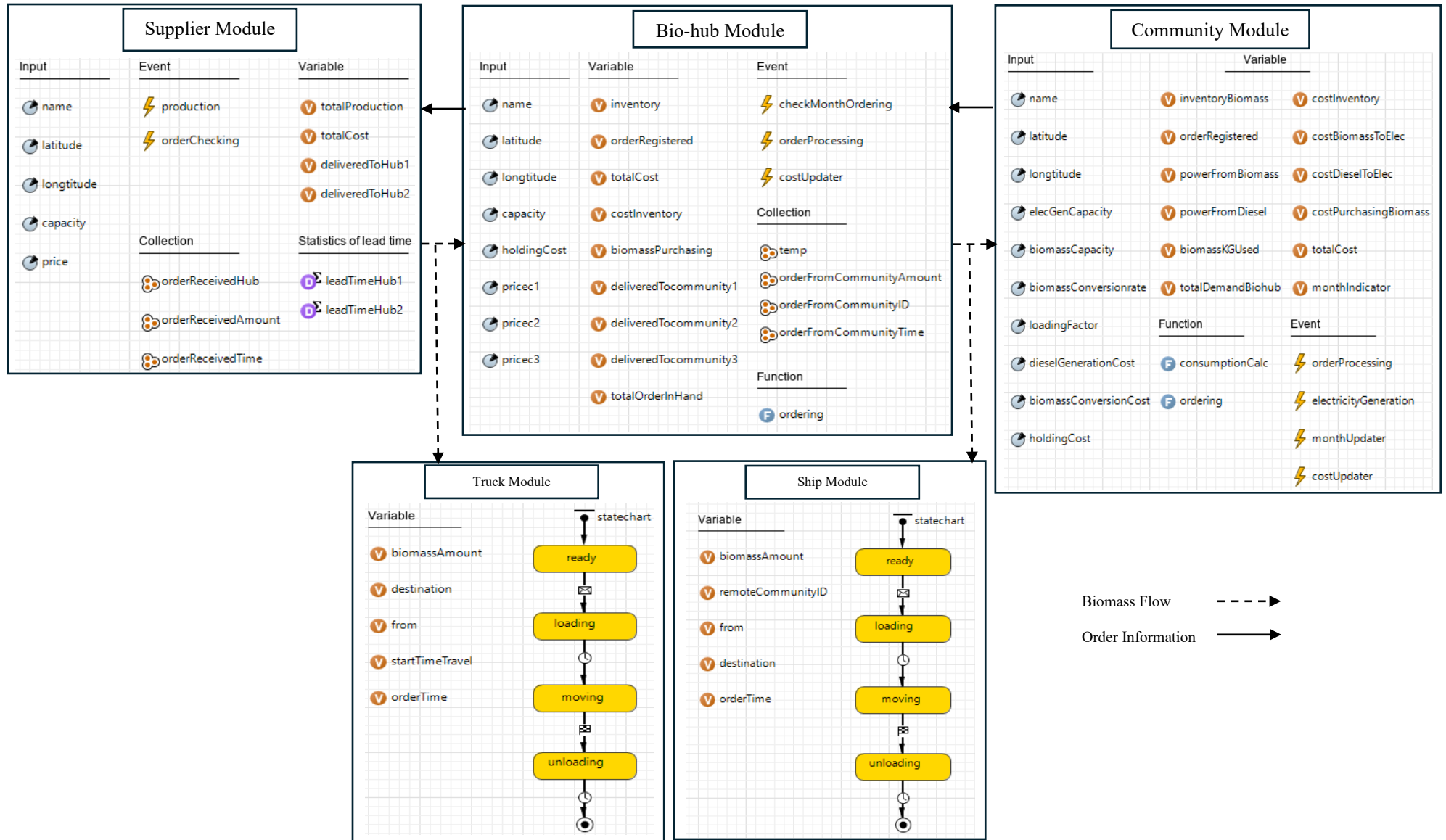


Figure 4.5. Developed Anylogic modules within the ABS model

Table 4.1. Nomenclature, key parameters and variables used in the ABS

Sets		
I	Set of suppliers indexed by $i \in I$	
K	Set of bio-hubs indexed by $k \in K$	
J	Set of communities indexed by $j \in J$	
r	Set of experiments run	
t	Time instant	
Parameters		Unit
C_i	Maximum production capacity of supplier i	kg/month
PS_{ik}	Biomass delivering cost from supplier i to bio-hub k	\$/kg
SC_k	Maximum storage capacity at bio-hub k	kg
PB_{kj}	Biomass delivering cost from bio-hub k to community j	\$/kg
HC_k	Holding cost at bio-hub k per unit of time	\$/kg
SC_j	Maximum local storage capacity at community j	kg
HC_j	Holding cost at community j per unit of time	\$/kg
γ_j	Levelised biomass-to-electricity conversion cost at community j	\$/kWh
δ	Levelised electricity generation cost from diesel (alternative fuel)	\$/kWh
D_j^t	Projected electricity demand of community j at t	kWh/month
f_j	Biomass-to-electricity conversion rate at community j	kWh/kg
C_j	Capacity of electricity generation from biomass at community j	kW
θ_j	Loading factor of electricity generation from biomass at community j	-
ELT_{ik}	Expected lead time of delivery from supplier i to bio-hub k	Minute
ELT_{kj}	Expected lead time of delivery from bio-hub k to community j	Minute
α	Service level threshold	%
ADT_{ik}	Available biomass delivery planning horizon from supplier i to bio-hub k	Month
ADT_{kj}	Available biomass delivery planning horizon from bio-hub k to community j	Month
EI_k	Emergency inventory level at bio-hub k	kg
Z_T	Truck Capacity	kg
Z_s	Ship Capacity	kg
S_T	Truck speed	kmh ⁻¹
S_s	Ship speed	kmh ⁻¹
L_T	Truck loading time	Minute
UL_T	Truck unloading time	Minute
L_s	Ship loading time	Minute
UL_s	Ship unloading time	Minute

Table 4.1 (Continued)

State Variables/ Outputs		Unit
x_{ik}^t	Biomass delivery from supplier i to bio-hub k at t	kg
y_{kj}^t	Biomass delivery from bio-hub k to community j at t	kg
EB_j^t	Electricity generated from biomass at community j at t	kW
ED_j^t	Electricity generated from diesel at community j at t	kW
OHB_k^t	On-hand inventory at bio-hub k at t	kg
OHC_j^t	On-hand inventory at community j at t	kg
OO_k^t	On-order inventory of bio-hub k at t	kg
OO_j^t	On-order inventory of community j at t	kg
B_j^t	Biomass used for electricity generation at community j at t	kg
$THCB_k^t$	Total biomass storage cost of bio-hub k at t	\$
TCB_k^t	Total cost of bio-hub k at t	\$
$THCC_j^t$	Total biomass storage cost of community j at t	\$
$TCEB_j^t$	Total cost of electricity generation from biomass at community j at t	\$
$TCED_j^t$	Total cost of electricity generation from diesel at community j at t	\$
TCC_j^t	Total cost of community j at t	\$
TC^t	Total cost of the BSC at t	\$
NT^t	Number of truckloads at t	-
NS^t	Number of shiploads at t	-

4.4.1. Simulation Modules and Algorithms

1) Supplier module: Suppliers are responsible for supplying biomass feedstock (i.e., wood pellet) based on the needs of bio-hubs. Thus, each supplier has its capacity and price offered to bio-hubs, including the material and transportation costs. Given the dispersed nature of biomass resources and the small scale of suppliers, replenishing feedstock from a single source might be infeasible. As such, biomass orders are split between several suppliers. As illustrated in Fig. 5, the central interaction within this module revolves around the processing and sending biomass orders to bio-hubs, given the available capacity of suppliers and the capacity constraints of trucks. Note that partial truckload shipments are not allowed in the logistic activities to avoid empty truck transportation. This ordering procedure is facilitated by an iterative “event” (i.e., check ordering) operating on a cyclical basis (i.e., hourly). It is noteworthy to mention that an “event” in the context of simulation modeling refers to a specific occurrence or incident within a simulation model that triggers a particular action or set of actions. Algorithm 4.1 describes this event ensuring biomass quantity purchased from the selected supplier forms full truckloads and does not exceed the

supplier's availability. Moreover, the lead time is calculated in this module, which refers to the duration between the initiation of an order and its completion, including waiting time for order processing, loading, transportation and unloading time.

Algorithm 4.1. Order processing in supplier module

Order Checking “Event”	
1	Load <i>total production</i> of suppliers Load <i>main. biomass transfer amount</i> by truck
2	if <i>order Received Amount</i> from bio-hub > 0
3	if <i>order Received Amount</i> from “bio-hub” ≥ <i>main. biomass transfer amount</i> by truck
4	if <i>total production</i> of suppliers ≥ <i>main. biomass transfer amount</i> by truck
5	Main. add_ trucks ()
6	Determine the index of bio-hub placed the order from <i>order received hub</i> collection
7	Determine the truck origin and destination
8	Send “ Move ” order to truck module
9	Update <i>total Production</i> of suppliers
10	Calculate <i>lead time</i> of suppliers

II) Bio-hub module: This module holds information of bio-hubs, such as geographical location, capacity, holding cost, and price offered to remote communities, including material and transportation costs. Bio-hubs are responsible for transforming order information and feedstock availability between suppliers and remote community modules. As shown in Algorithm 4.2, the system first verifies the receipt of orders from the communities. Upon confirmation, the order processing phase starts via the corresponding cyclic event. Subsequently, the module computes the quantity of orders to be placed with suppliers. The supplier selection process is then executed, prioritizing the biomass supply sources with adequate availability. In the same condition, the supplier offering a cheaper price is selected. The total cost of the bio-hub module calculated in this algorithm can be derived from the Equation (4.1).

$$TCB_k^t = \sum_{t=0}^T \sum_{i=1}^I \sum_{k=1}^K x_{ik}^t \cdot PS_{ik}^t + \sum_{t=0}^T \sum_{k=1}^K OHB_k^t \cdot HC_k \quad (4.1)$$

Algorithm 4.2. Order processing and cost calculation in bio-hub.

1. Check Ordering “Event”	
1.1	For each bio-hub
1.2	Load <i>capacity</i> , <i>inventory</i> , and <i>order registered</i>
1.3	if <i>amount</i> = <i>capacity</i> – <i>inventory</i> – <i>order Registered values</i> > 0
1.4	Add the index of this bio-hub to <i>order Received Hub</i> in supplier module
1.5	Load Ordering function
1.6	Ordering (<i>amount</i>)
1.7	Update <i>order Registered</i>
2. Ordering “Function”	
2.1	For each supplier
2.2	if suppliers. <i>total Production</i> > <i>amount</i>
2.3	Add this supplier to <i>temp</i> collection
2.4	if temp. size () > 0
2.5	Load the price offered by this supplier from the supplier module
2.6	Determine the supplier offering min price
2.7	Select the supplier
2.8	if offered price of suppliers in <i>temp</i> is equal
2.9	Select supplier index = uniform_discr (0, number of suppliers)
2.10	Add <i>amount</i> to <i>order Received Amount</i> in supplier module
2.11	Add time of placing order to <i>order Received Time</i> in supplier module
3. Order Processing “Event”	
3.1	Load main. <i>bio-hub to remote community month Start</i> and main. <i>bio-hub to remote community Month Finish</i>
3.2	if (get Month () ≥ main. <i>bio-hub to community month Start</i> && get Month () ≤ main. <i>bio-hub to community Month Finish</i>)
3.3	if <i>order From Community Amount. Size</i> () > 0
3.4	if <i>order From Community Amount</i> > main. <i>biomass transfer amount by ship</i>
3.5	if <i>inventory</i> > main. <i>biomass transfer amount by ship</i>
3.6	Main. add_ ships ()
3.7	Determine the index of remote community placed the order from <i>order From Community Id</i> collection
3.8	Determine the ship origin and destination
3.9	Send “ Move ” order to ship module
3.10	Update <i>order From Community</i> amount
3.11	Update <i>inventory</i> of bio-hubs
3.12	Update <i>delivered To Community 1</i> , <i>delivered To Community 2</i> , and <i>delivered To Community 3</i>
3.13	Calculate the <i>lead time</i> of bio-hubs

Algorithm 4.2 (Continued)

4. Cost updater “Event”	
4.1	For each bio-hub
4.2	Calculate biomass purchasing cost from suppliers
4.3	Calculate inventory cost
4.4	Update <i>main. total cost</i>

III) Remote community module: Remote communities are the end-users of the proposed BSC, while they are responsible for electricity generation from either biomass or diesel to meet the energy demand in these communities. As such, information such as the capacity of biomass electricity generation facilities, loading factor in communities, and biomass conversion rate is needed to activate the electricity generation procedures. Moreover, given the logistical challenges linked with sea shipping, there exists a possibility for stocking biomass within local inventory facilities, ensuring availability during periods when ordering becomes unfeasible. Therefore, the cost of this module can be calculated based on the levelized cost of electricity from biomass and diesel, and holding cost of biomass, derived from Equation (4.2).

$$\begin{aligned}
 TCC_j^t = & \sum_{t=0}^T \sum_{k=1}^K \sum_{j=1}^J y_{kj}^t \cdot PB_{kj}^t + \sum_{t=0}^T \sum_{j=1}^J OHC_j^t \cdot HC_j \\
 & + \sum_{t=0}^T \sum_{j=1}^J EB_j^t \cdot \gamma_j + \sum_{t=0}^T \sum_{j=1}^J ED_j^t \cdot \delta
 \end{aligned} \tag{4.2}$$

The components of the remote community module have been illustrated in Fig. 5. Associated events and functions, including energy generation, ordering procedure and cost calculation in communities are outlined in Algorithm 4.3.

Algorithm 4.3. Energy generation, ordering procedure and cost calculation in remote communities

1. Order processing “Event”	
1.1	if (get Month () $\geq$ <i>main. bio-hub To Community Month Start</i> && get Month () $\leq$ <i>main. bio-hub To Community Month Finish</i>)
1.2	Load Ordering function
1.3	for each remote community
1.4	Define amount = <i>biomass Capacity</i> – <i>inventory Biomass</i>
1.5	if amount > 0 && <i>order Registered</i> = 0
1.6	Ordering (amount)
1.7	Update <i>order Registered</i>

Algorithm 4.3 (Continued)

2. Ordering “Function”	
2.1	for each <i>bio-hub</i>
2.2	if (<i>main. biohubs. get (). inventory – main. biohubs. get (). total Order In Hand</i>) > <i>amount</i>
2.3	<i>main. biohubs. get (). order From Community Amount. add(amount);</i>
2.4	Add the index of this bio-hub to <i>order From Community ID</i> in bio-hub module
2.5	Add the time of ordering to <i>order From Community Time</i> in bio-hub module
2.6	Update <i>total Order In Hand</i> in bio-hub module
3. Electricity consumption calculation “Function”	
3.1	Calculate <i>hourly electricity needed</i>
3.2	For each remote community
3.3	Calculate <i>max electricity generation from biomass = electricity Generation Capacity * loading Factor;</i>
3.4	Define <i>quantity = min (max electricity generation from biomass, hourly electricity needed);</i>
3.5	Calculate <i>Kg biomass needed = min ((quantity / biomass conversion rate) / loading factor, inventory Biomass);</i>
3.6	Update <i>quantity = min (quantity, Kg biomass needed *biomass conversion rate * loading factor);</i>
3.7	if <i>Kg biomass needed = 0</i>
3.8	Generate electricity from diesel
3.9	else generate electricity form biomass
3.10	Calculate remain electricity needed
3.11	Generate remain electricity needed from diesel
3.12	Update <i>power From Biomass</i>
3.13	Update <i>power From Diesel</i>
3.14	Update <i>inventory Biomass</i>
3.15	Update <i>biomass Kg used</i>
4. Electricity generation “Event”	
4.1	Switch (<i>month indicator</i>)
4.2	Load <i>electricity consumption calculation Function</i>
4.3	<i>consumption calculation (month indicator)</i>
5. Cost updater “Event”	
5.1	For each remote community
5.2	Calculate biomass purchasing cost from bio-hubs
5.3	Calculate inventory cost
5.5	Calculate cost of electricity generation from biomass
5.6	Calculate cost of electricity generation from diesel
5.7	Update <i>main. total cost</i>

IV) Truck and ship modules: The transportation means of the proposed BSC are trucks (from suppliers to bio-hubs) and ships (from bio-hubs to remote communities). As shown in Fig. 5, whenever trucks and ships are called, they are placed in a ready state and travel time begins. In the

loading state, destination information and speed are provided to these agents. Upon their arrival at facilities (i.e., bio-hubs and remote communities), the unloading process is started. Subsequently, the inventory levels and registered orders for these facilities are updated in a way that on-order inventory is reduced, while on-hand inventory is increased by the quantity equivalent to one truckload/shipload. The operating time for loading and unloading activities is also calculated given the loading and unloading time of the agents.

4.4.2. Disruption Modeling

After modeling the behavioral rules of entities and configuring the input parameters, disruption scenarios are defined. The inputs of these scenarios are network topology and settings for disruption generation, which are injected into the simulation model combined with the main modules of the proposed SC and associated operations. In fact, the simulator is provided with scenario settings as input, including the quantity of nodes/links to be disrupted, the intensity, and duration of disruptions for each node in the network, as well as the structure of the mitigation strategies. Subsequently, these disruption scenarios are simulated over a defined planning horizon (e.g., one year). The disruption simulator is responsible for efficiently conducting the necessary simulations and passing the observed outcomes to the resilience measurement indicators to characterize overall network resilience, considering its multifaceted perspective.

In SCs under uncertainty, various resilience strategies can be integrated into the network design to facilitate the quick restoration of systems to their initial state or reach a more desirable state. As noted in the previous sections, bio-hubs are the central storage and distribution nodes within the proposed network. However, their performance and consequently the entire BSC can be significantly impacted by disruptions, particularly those related to feedstock availability. Therefore, any failure in bio-hub operations can significantly affect the downstream echelons in terms of bioenergy generation. To overcome this issue, mitigation strategies are considered to restore the bio-hub's performance in the case of disruption.

Within the simulation model, the operational state of these bio-hubs is characterized as “disrupted” if the service level indicator (defined as the proportion of on-time delivered orders to the total number of orders) falls below a certain threshold (i.e., the parameter of the simulation model). Conversely, operations are recovered if this service level surpasses the threshold. In this study, simulation experiments have been conducted with two recovery policies, i.e., i) backup

inventory and ii) backup supplier, which are important resilience strategies in the literature of the SCR to mitigate the effect of disruptions (Hosseini et al., 2019). Both strategies are proactively adopted, while their activation is contingent upon the occurrence of a disruption and the predefined threshold. In the backup inventory scenario, bio-hubs always maintain a predetermined quantity of biomass as a safety stock to meet the needs of communities under unplanned situations. In the other scenario, a backup supplier is set to operate during disruption time; consequently, both capacity and costs significantly differ from those of regular suppliers (Moosavi and Hosseini 2021). The parameters associated with these two strategies are also fed into the simulation model to implement the disruption scenarios.

4.4.3. Resilience Measurement

To address the limitations of existing metrics in literature, a set of indicators grounded in three core resilience capacities is adopted. In this study, six metrics of reliability (M1), preparedness (M2), responsiveness (M3), persistence (M4), resourcefulness (M5), and recovery time (M6) are simultaneously considered. The first two metrics are related to the absorptive capacity, and the last one indicates restorative capacity. M1 and M2 respectively refer to the time-period that the network performs its tasks under specified circumstances and the amount of reduction in performance under disruption, while M6 indicates recovery duration. The remaining metrics illustrate the adaptive capacity of resilience. More precisely, M3 shows the time-period that system performance is declining, M4 represents the maximum reduction in system performance, and M5 denotes the timeframe between the end of disruption effects and the start of the recovery process. (Habibi et al., 2023b). To quantify these metrics, three structural indicators are employed, which are based on the three network characteristics of density, criticality, and connectivity (Dixit et al., 2020):

i) Network Density (ND): ND is referred to the ratio of active non-disrupted links to the total number of potential links within the network (see Equation (4.3)). ND is an important structural indicator in assessing the effect of disruption on the network, as it decreases with the propagation of disruptions (Son et al., 2021). Literature mentioned that the number of healthy nodes adopted in the literature cannot correctly reflect the SCR. Indeed, apart from disruptions, nodes may also be withdrawn from the network due to various reasons, such as the termination of contracts with suppliers (Habibi et al., 2023b). As such, relying solely on healthy nodes could be misleading.

$$ND = \frac{\text{Number of existing (healthy) links}}{\text{Total number of potential links}} \quad (4.3)$$

ii) The size of the largest connected component (SLCC) in the network: Throughout disruptions, the network may become segmented into several separate sub-networks. The SLCC serves as a measure to determine the level of fragmentation within the network. It indicates the number of facilities which are not disrupted within the largest sub-network. A larger value of this indicator denotes that disruption has had a lesser impact on the network (Hou et al., 2018; Zhao et al., 2022).

iii) Max degree centrality (MDC): Degree centrality measures the number of connections a node has to other nodes in the network. The node with the maximum degree centrality is the one that has the highest number of directed connections or edges (Son et al., 2021). When a network is disrupted, the MDC decreases as the nodes lose their connections gradually. Subsequently, it increases during the recovery phase until it reaches its normal condition. Considering the directed structure of the network, the MDC is defined as the sum of maximum in-degree and out-degree centralities (Habibi et al., 2023b), as shown in Equation (4.4):

$$MDC = \text{Max (indegree centrality of nodes)} + \text{Max (outdegree centrality of nodes)} \quad (4.4)$$

This study uses the above-mentioned concepts to calculate three resilience capacities considering recovery strategies. Hence, DMs can investigate how network characteristics, disruptions in nodes and links, and ripple effects influence BSC dynamics. However, focusing only on structural indicators may neglect the operational consequences of disruption and in particular, resilience strategies (Taghizadeh et al., 2021). As such, electricity generated from biomass and diesel are analyzed to assess the operational performance of communities. The main objective of the proposed BSC is to supply biomass to these off-grid communities and strategic plan for its substitution with diesel. Therefore, bioenergy generation is a very important indicator that requires investigation under each scenario. Besides, financial indicators such as the cost of bio-hubs, communities, and the total cost of the system are computed to provide insights into the cost profile of these scenarios. These metrics collectively contribute to a comprehensive understanding of the BSC's overall resilience, facilitating informed decision-making and planning for mitigating disruptions and enhancing the performance of the network.

4.5. Discussions

To allow for effective representation, this section starts by explaining disruption experiments and outlining modelling assumptions, followed by presenting results of the simulation model. Afterwards, managerial and practical implications are discussed.

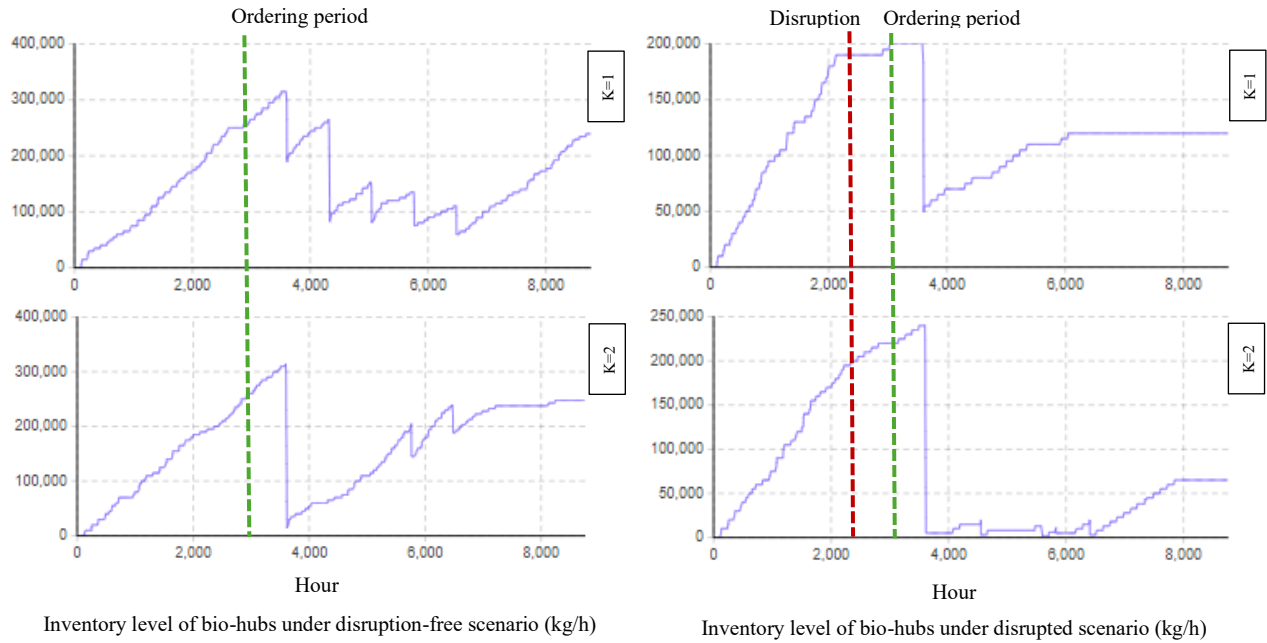
4.5.1. Results

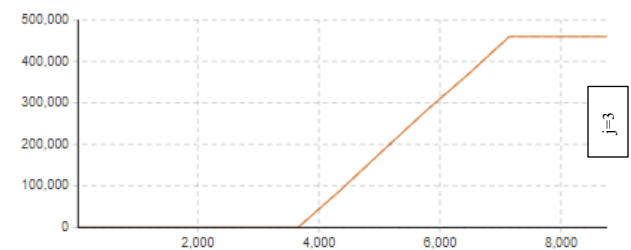
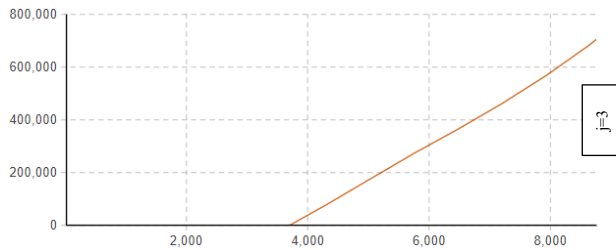
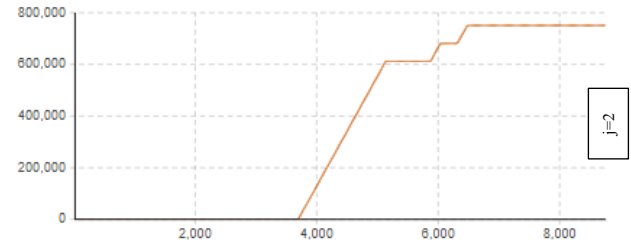
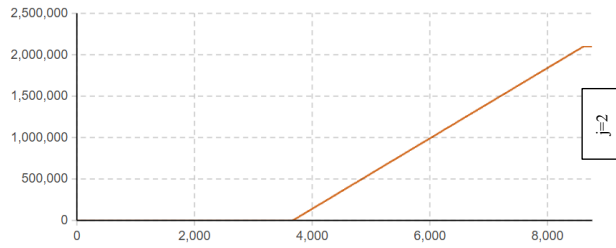
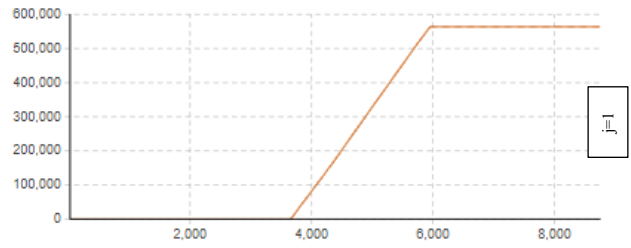
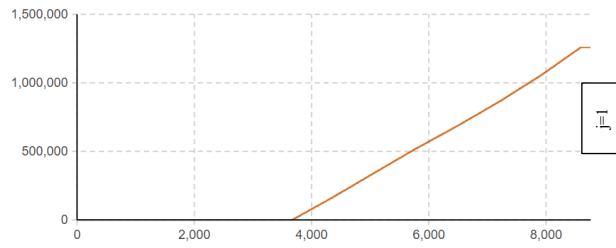
The ABS serves as the primary approach of this study for the resilience assessment of the proposed BSC. In this model, after configuring and initializing the network with the appropriate operating rules and parameters, the entire supply network is simulated for a duration of one year, starting from 1st January until 31st December with a two-week warm-up period. To introduce disruptions, “events” are designed within the simulation model to alter the operational capacity of suppliers at designated times with predetermined levels. Such disruption is very common in BSCs due to the reliance of feedstock availability on various factors, including weather conditions, soil quality, regulatory changes, transportation disruptions, and technological issues. The supply disruption scenarios are scheduled in the middle of the simulation planning horizon to avoid the noise caused by the simulation experiment start (Ivanov, 2019) and capture the dynamicity of logistical constraints in the proposed BSC and their impacts on bio-hubs and communities’ operations. As such, disruptions are introduced during the transportation period from bio-hubs to remote communities. In this scenario, it is assumed that two of the suppliers are partially disrupted, one is fully disrupted, and the next one is still healthy. Designing such a scenario can illustrate the challenges that bio-hubs and communities would face in maintaining operational efficiency under unexpected events. Moreover, to capture logistical risks and delays, loading, unloading, and travel time are considered stochastic parameters. These assumptions collectively could result in outputs which are closer to reality.

The activation of mitigation tactics relies on the service level of bio-hubs. As such, it is assumed that the state of bio-hubs is considered as disrupted if the service level falls below 70% and is considered as recovered if the service level exceeds 85% (i.e., average service level of the network under disruption-free scenario). In this study, two benchmark scenarios are executed for validation purposes of the proposed agent-based model. The first scenario involves simulating a disruption-free condition, where no disruptions are introduced into the system. The second

scenario simulates disruptions without the implementation of any mitigation strategies. These scenarios serve as a benchmark for comparison against the model's performance under adopting mitigation strategies (Ivanov, 2022; Saisridhar et al., 2024). Figure 4.6 demonstrates the operational performance of bio-hubs and communities under these two scenarios.

Statistical tests are also employed to validate the obtained results, investigating significant differences among the recovery strategies in terms of performance indicators. These statistical analyses are conducted for each performance metric separately, with a confidence interval of 95% being considered. Since the samples from the scenarios are not related, the assumption about independent samples held true. Furthermore, the sample size for both strategies (50 runs) exceeded 30, satisfying the conditions of the Central Limit Theorem (Ott and Longnecker, 2016), ensuring the normal distribution of sample means and results convergence (Correa-Martinez and Seck, 2023; Saisridhar et al., 2024).





Electricity generation from biomass at communities under disruption-free scenario (kW/h)

Electricity generation from biomass at communities under disrupted scenario (kW/h)

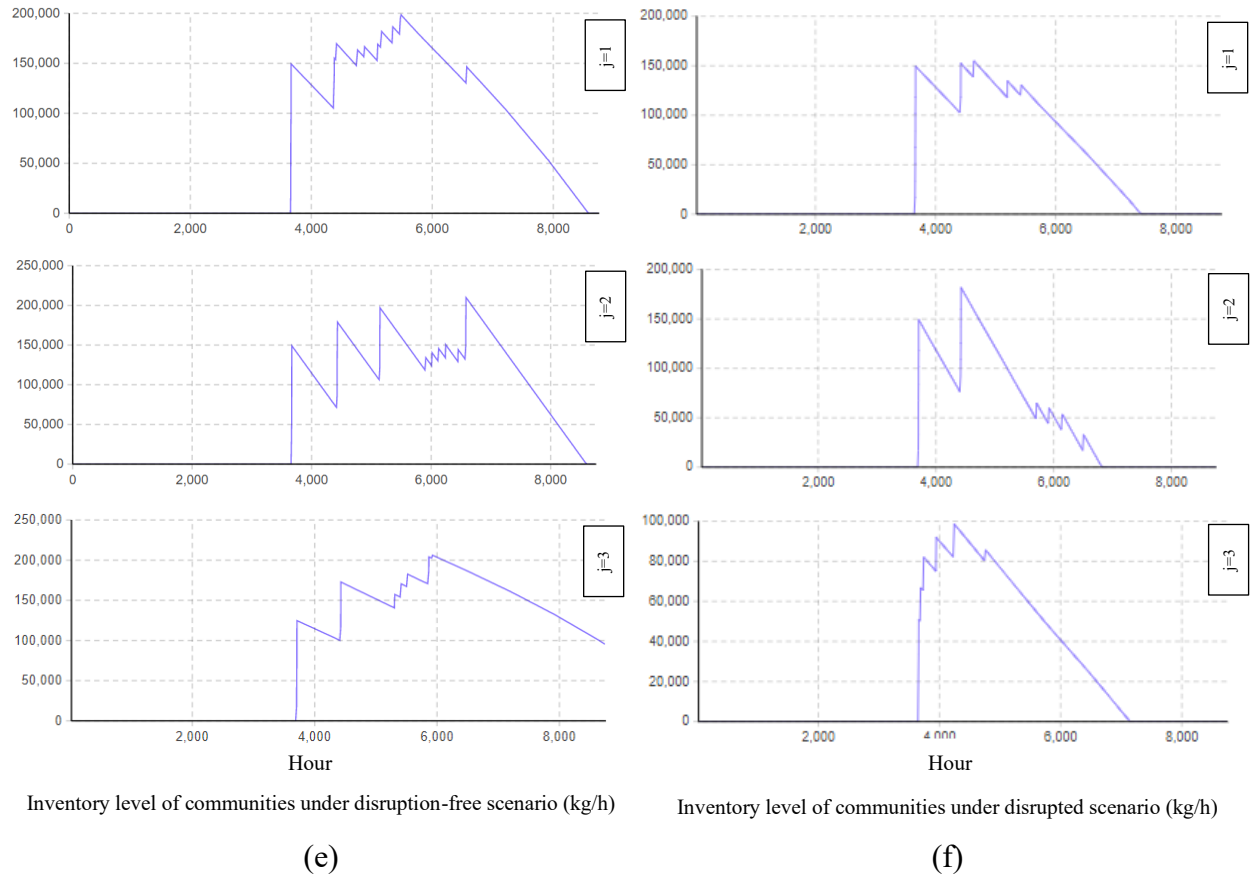


Figure 4.6. Snapshots of operational performance of bio-hubs and communities

The F-test was employed to assess whether the population exhibited equal variances. When variances are equal, the 2-sample t-test utilizing pooled variances is applied, whereas when variances are unequal, the 2-sample t-test utilizing separate variances is employed (Ott and Longnecker, 2015; Akhtari et al., 2019).

The experiments of this study have been performed with the parameters explained in Table 4.2. Several of these parameters have been approximated from the literature (Mafakheri et al., 2021; Taheri and Taft, 2024; Akhtari et al., 2019; Gautam et al., 2017), and information about communities such as logistical data and fuel cost were extracted from NEAS (2024) and Lovekin and Heerema (2019).

Table 4.2. Parameters of the simulation model

Parameter	Value	Parameter	Value
C_i	(33,300, 34,000, 30,700, 31,000) kg/month	δ	1.14 \$/kWh
PS_{ik}	(0.205, 0.201, 0.200, 0.220) \$/kg	f_j	(4.7, 4.8, 4.6) kWh/kg
SC_k	(350,000, 400,000) kg	C_j	(500, 500, 500) kW
PB_{kj}	(0.362, 0.409) \$/kg	θ_j	(0.80, 0.85, 0.80)
HC_k	(0.03, 0.03) \$/kg	ADT_{ik}	All year
SC_j	(300,000, 300,000, 250,000) kg	ADT_{kj}	May - September
HC_j	(0.115, 0.115, 0.115) \$/kg	Z_T	5000 kg
γ_j	(0.046, 0.044, 0.048) \$/kWh	Z_s	17000 kg
S_T	U [50, 100] kmh ⁻¹	S_s	30 kmh ⁻¹
L_T	U [60, 120] minutes	L_s	U [120, 180] minutes
UL_T	U [60, 120] minutes	UL_s	U [120, 180] minutes
D_j^t (kWh)			
	KA($j=1$)	SA($j=2$)	IV($j=3$)
January	246,900	465,900	133,300
February	226,500	427,400	122,300
March	219,900	414,900	118,700
April	186,300	351,500	100,500
May	171,900	324,400	92,800
June	171,000	322,600	92,300
July	180,900	341,200	97,600
August	179,700	339,100	97,000
September	168,700	318,300	91,100
October	178,700	337,100	96,400
November	194,800	367,500	105,100
December	216,800	409,000	117,000

Figure 4.7 provides an overview of the network's behavior throughout the simulation period. This figure demonstrates the operational dynamics of the proposed network under two distinct recovery strategies. Nodes and links experiencing disruption are denoted in red, whereas successfully recovered elements are highlighted in green. As shown in the second column of this figure, the SCN normally acts from the start of the simulation until the disruption occurs (at $t = 2184$).

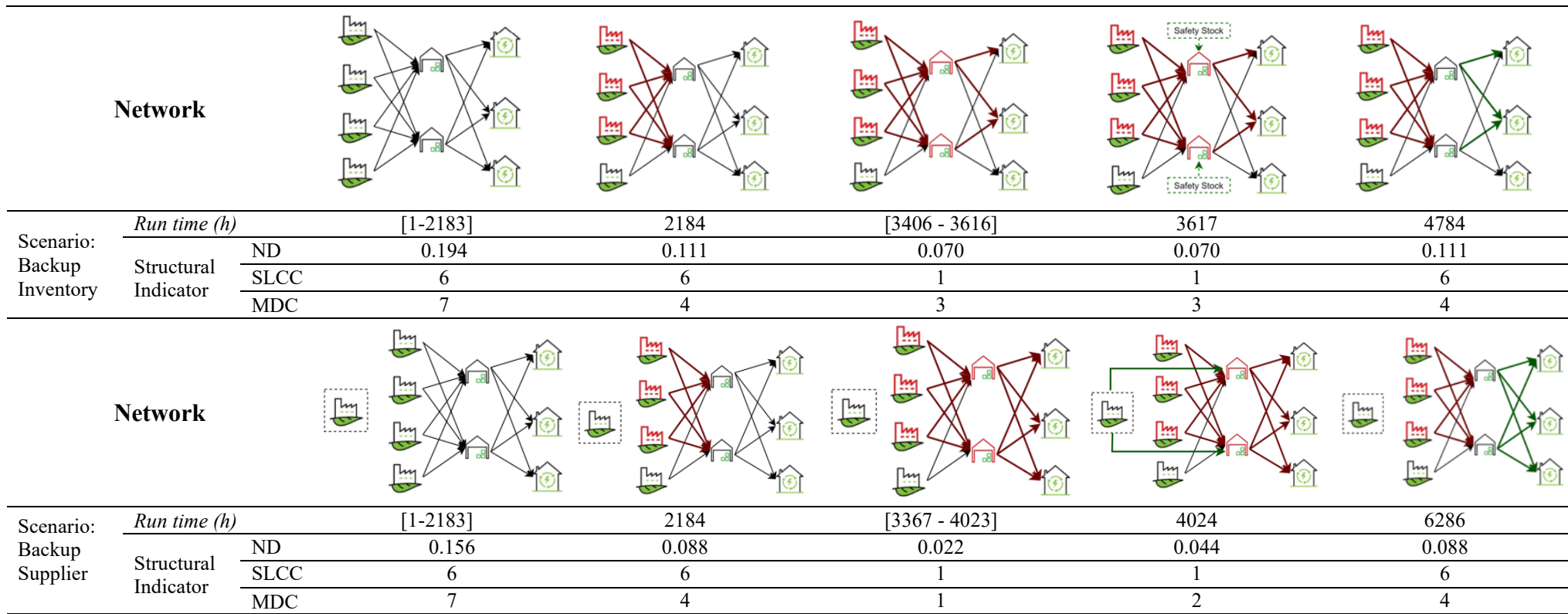


Figure 4.7. Disruption and recovery processes and associated structural indicators

The third column illustrates the time that disruption starts to propagate to another node, and the condition remains unchanged until the recovery strategies are activated (fourth column) and the system achieves stable condition at the time shown in last column of Figure 4.7.

To calculate the mentioned six metrics (i.e., M1 to M6) of each indicator, first, the resilience triangle is extracted, with the x-axis denoting time and the y-axis representing the indicator, i.e., ND, SLCC, and MDC. For this purpose, the results obtained from the simulation model, as illustrated in Figure 4.7, provide information on both the time and values of the indicators. Then based on their definitions, each metric can be calculated. It is worth noting that, as the structural indicators and their associated metrics differ in range, the normalized values of M1 to M6 for each indicator are computed to enable a comparative analysis of resilience and determine which recovery scenario demonstrates superior resilience characteristics. Table 4.3 and Figure 4.8 depict the outcomes of this comparative analysis.

Table 4.3. The normalized resilience metrics related to structural indicators.

Structural indicator	Mitigation scenario	Metrics					
		M1	M2	M3	M4	M5	M6
ND	Backup Inventory	0.350	0.427	0.194	0.639	0.034	0.150
	Backup Supplier	0.350	0.435	0.200	0.859	0.105	0.360
SLCC	Backup Inventory	0.542	0	0	0.830	0.034	0.150
	Backup Supplier	0.535	0	0	0.830	0.105	0.360
MDC	Backup Inventory	0.350	0.428	0.194	0.571	0.034	0.150
	Backup Supplier	0.350	0.428	0.200	0.857	0.105	0.360

To facilitate a comparison of the mitigation strategies, the main network structure remains consistent. Consequently, as expected, the system's behavior remains unchanged prior to the propagation of disruption. Table 4.3 supports this observation by demonstrating that both strategies have similar reliability (i.e., M1), preparedness (i.e., M2), and responsiveness metrics (i.e., M3). According to M4 (i.e., persistence) metric, the depth of disruption's effects in the case that the recovery scenario is a backup supplier is almost 1.5 times as higher as in the other scenario regarding ND and MDC. Hence, the backup supplier strategy demonstrates lower persistence. The results obtained from the resourcefulness measure (i.e., M5) indicate that the start of recovery is almost 3 times faster than the backup supplier scenario across all performance indicators.

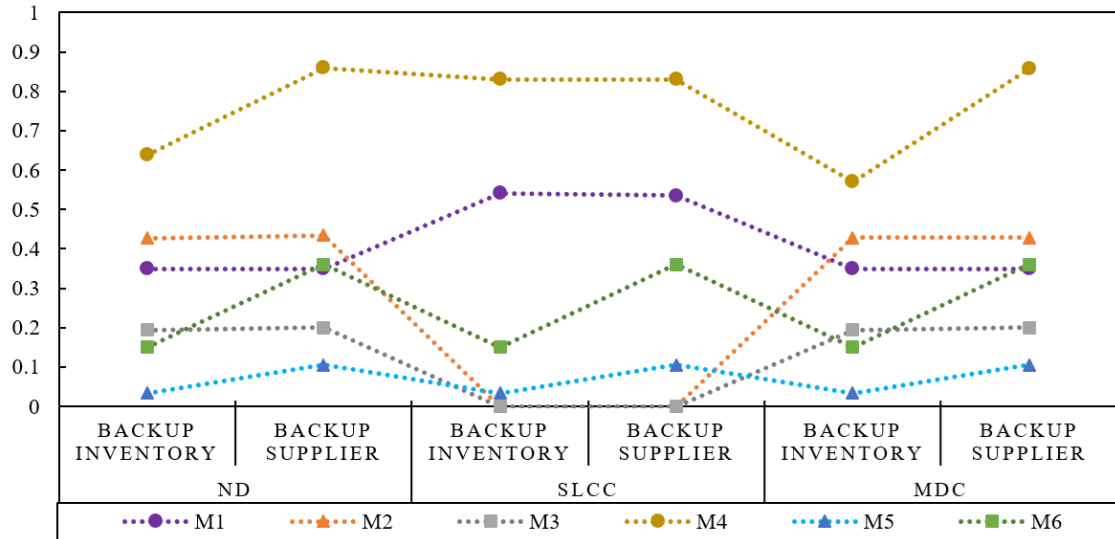


Figure 4.8. Performance indicators of ND, SLCC and MDC

The results obtained from the recovery time measure (i.e., M6) indicate that the backup inventory strategy exhibits a faster recovery speed (2.5 times more) compared to the other one. Due to the less depth of disruption's effect in this scenario, it is not surprising that it can return to the normal performance level faster. Considering the logistical challenges associated with biomass transportation to communities, investing in a mitigation strategy is crucial to ensure the rapid restoration of the entire system to standard levels with minimal performance loss. Therefore, in the proposed case study, having a backup inventory as safety stock, would assist bio-hubs in mitigating the impacts of disruptions, which is consistent with their primary role as inventory storage facilities.

In addition to the six metrics calculated for each of the three structural indicators, the operational indicators demonstrate the impact of these strategies on the operational performance of the network. Given that the electricity generated from biomass in the disruption-free scenario is 3,735,298 kW on average, the backup inventory strategy could compensate 85% of the disruption effect leading to 3,178,157 kW electricity generation; however, in the backup supplier scenario, this amount is decreased to 2,733,99 kW. It is noteworthy that the lack of either recovery scenario would lead to a reduction in bioenergy share to 2,504,040 kW, highlighting the necessity of these strategies. Figure 4.9 illustrates the amount of electricity generated from either biomass or diesel under each scenario.

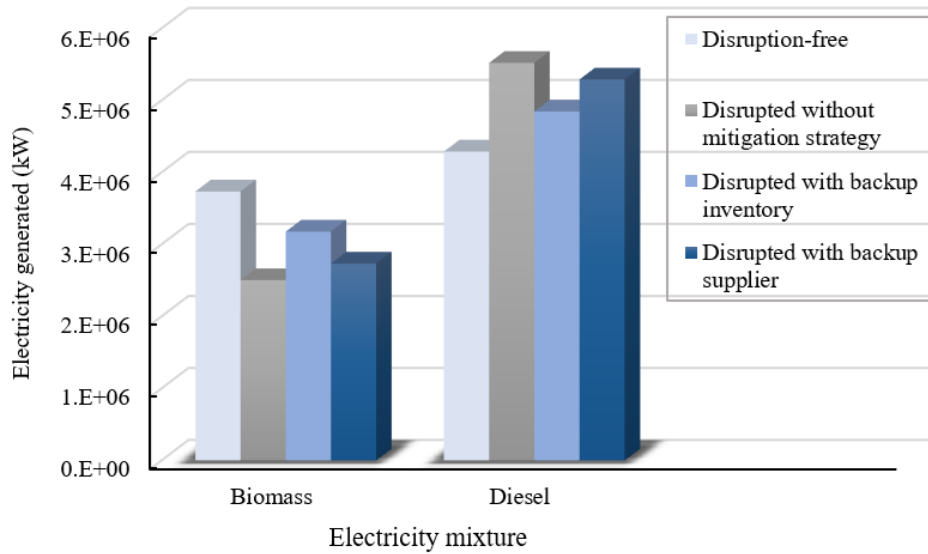


Figure 4.9. Total electricity generation

In terms of total cost, maintaining safety stock incurs inventory costs for both bio-hubs and whole BSCs compared to scenarios where no extra inventory is held. As such, it is not surprising to have a higher total cost in the backup inventory scenario since the main function of such hubs is holding inventory to deal with unexpected situations. This observation is evident in Figure 4.10, where the bio-hubs constitute the major portion of the total cost of the BSC. Furthermore, in the case of disruption with no mitigation strategy, the total cost of communities is higher than in other scenarios. The reasoning behind this is the increased use of diesel for electricity generation, which is more expensive compared to biomass. For the same reason, the cost of communities in the backup supplier scenario is higher than the backup inventory.

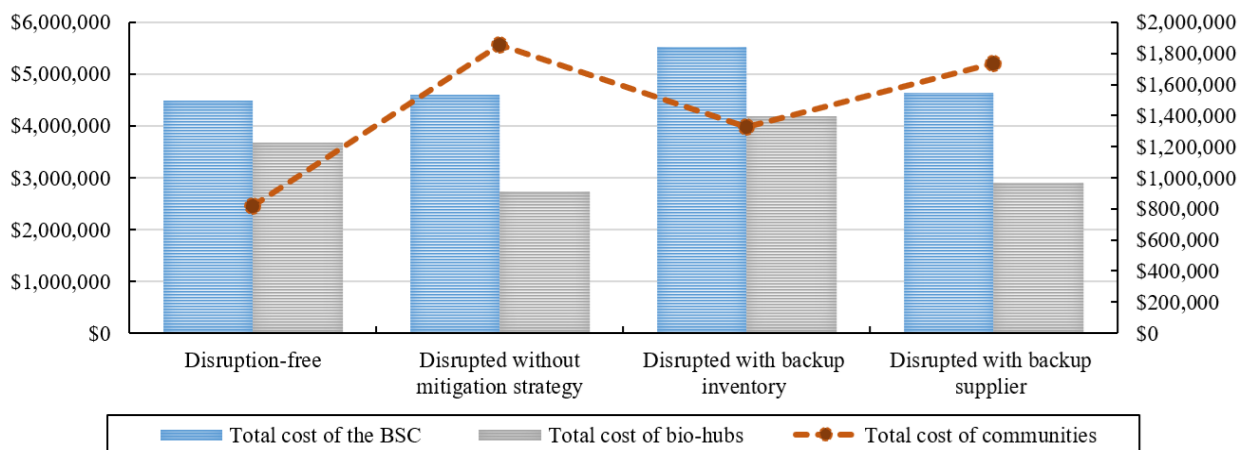


Figure 4.10. Cost profile of the proposed BSC

In addition to the cost and biomass share in electricity generation, the simulation model can also provide insights into the lead time of bio-hubs. As shown in Figure 4.11, the average lead

time remains comparable between the disruption-free scenario and backup inventory scenario, albeit with a higher biomass share and lower cost in the former. Furthermore, the increased lead time observed in the backup supplier scenario, as well as disrupted without mitigation strategy scenario, can be attributed to the lack of enough feedstock in bio-hubs to meet orders on time. These outputs support the results illustrated in Figure 4.7 in terms of bio-hubs' disruption. In the backup inventory scenario, the intensity of disruption propagated from the second bio-hub to communities is lower compared to the first one. Conversely, in the backup supplier scenario, both bio-hubs propagate disruption to communities. Despite all these differences, lead time alone could not be adequate for analyzing SC status, while such information can also be utilized to configure parameters within the simulation model, as demonstrated in this study. To conclude, these findings collectively contribute to a comprehensive understanding of the various facets of disruptions and mitigation strategies within the SC. This holistic perspective empowers DMs to proactively assess and address potential challenges, thereby enhancing the resilience and efficiency of the system.

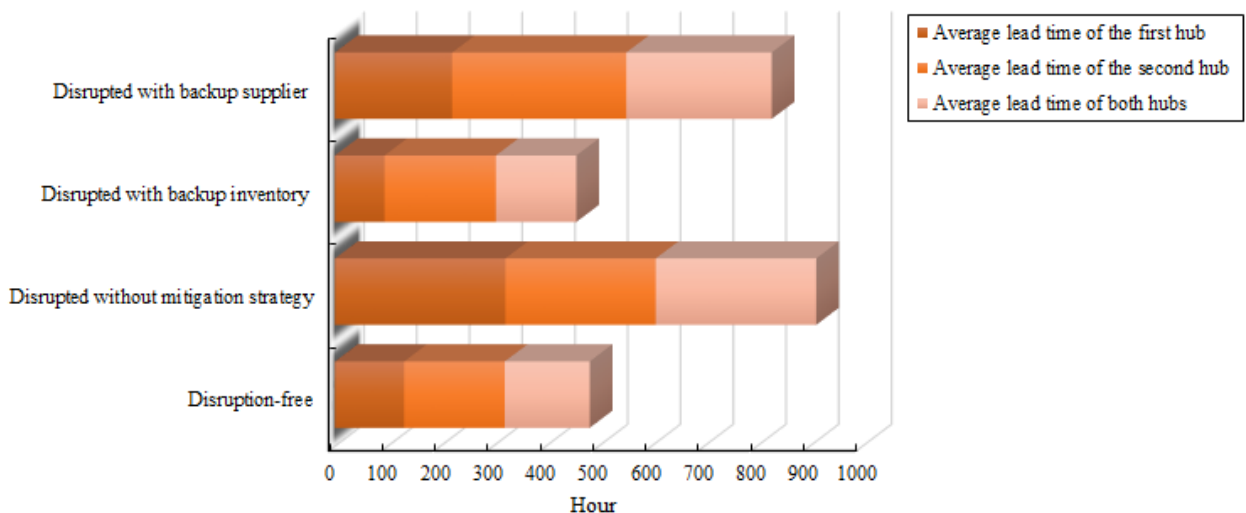


Figure 4.11. Lead time of bio-hubs

4.5.2. Practical and Managerial Implications

In Canada, over 280 communities, are disconnected from the North American electrical grid and lack natural gas distribution pipelines, relying predominantly on costly diesel-fired generation for energy needs (CER, 2018). This reliance brings significant challenges, including high energy costs and logistical complexities in fuel transportation, leading to economic burdens, and hindering development (Sadaghiani et al., 2023). Therefore, this study has sought to provide tailored research and practices addressing the unique energy security needs of

remote communities. In this regard, the outputs of this research can be employed by policymakers and managers to foster sustainable, resilient, and reliable energy solutions. Based on the results of this study on three remote communities, biomass has the potential to serve as the primary energy source for these areas in long-term planning. Figure 4.12 illustrates the electricity production derived from biomass under disruption-free conditions over a period of 10 years. It reveals that biomass could potentially account for nearly 60% of the energy supply in the long run. This highlights the importance of planning a resilient and reliable BSC to ensure consistent energy provision and mitigate the impacts of potential disruptions which are common in BSCs.

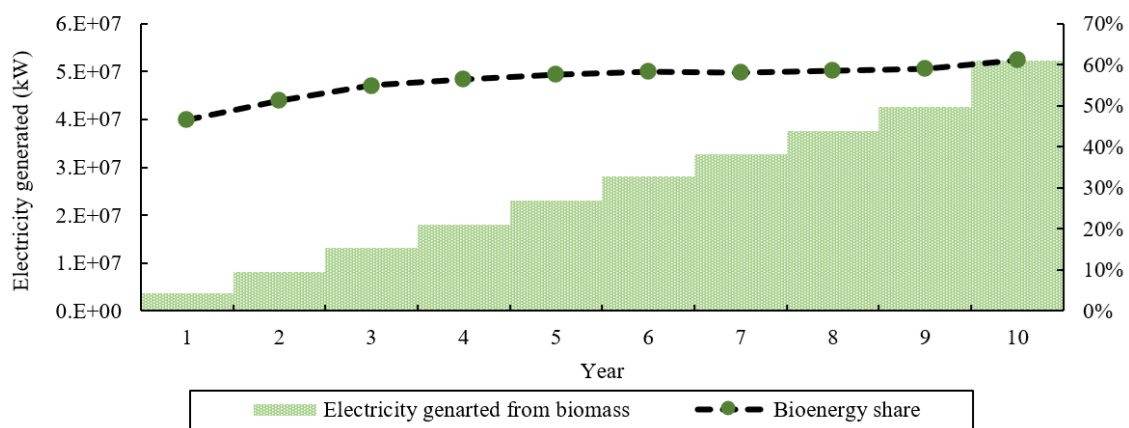


Figure 4.12. Biomass shares in the three communities in long-term planning

This research demonstrated how operational planning of bio-hubs can alleviate the impacts of disruptions and contribute to the sustained operation of the proposed BSC. Both recovery strategies offer solutions for supply shortages, but leveraging backup inventory in bio-hubs could potentially enhance bioenergy generation within communities. Nonetheless, maintaining prepositioned inventory is costly, thereby increasing the total cost of the BSC. Despite this, the cost of communities decreased as a result of increased electricity generation from biomass, which is more cost-effective compared to diesel. Table 4.4 presents a comparison of how various inventory levels affect the cost profile and the amount of biomass-derived electricity generation under disruption scenarios. Two scenarios are analyzed: one involving the disruption of three suppliers (considered large-scale), and the other where only one supplier is disrupted. Results illustrate that maintaining additional inventory in bio-hubs can compensate for the effects of disruption, depending on its scale. These findings underscore the importance of inventory planning for bio-hubs, emphasizing the necessity to achieve a balance between the costs incurred by bio-hubs and communities, while ensuring sufficient feedstock supply to meet community demand. It should be noted that, as cost outputs are dependent on the cost

parameters considered in this study, any changes to these inputs could lead to substantial changes in the final cost profiles of these strategies. However, it is evident that there is a necessity to create a balance between the expenses associated with maintaining additional biomass inventory and the costs of electricity generation from diesel. Consequently, DMs should thoroughly assess the implications of adopting a particular strategy from different angles, as illustrated in this research. More precisely, the suggested framework enables managers and DMs to quantitatively assess the impact of adopting any network configurations and recovery strategies from structural, operational, and financial perspectives. Structurally, it evaluates resilience by analyzing the absorptive, adaptive, and restorative capacities. Operationally, it evaluates how adopting various alternatives affects network performance, while financially, it examines their cost-effectiveness. This multidimensional analysis provides DMs with a robust basis for optimizing SCNs, ensuring they are both resilient to disruptions and economically viable.

Table 4.4. Sensitivity analysis for different feedstock inventory level in bio-hubs

Scenarios	Total cost of communities (\$)	Total cost of the BSC (\$)	Total electricity generated from biomass (kW)
Disruption-free	820,585	4,494,020	3,735,298
Large-scale disruption (current scenario)			
Disrupted	1,856,405	4,594,985	2,504,040
10% extra inventory	1,430,713	4,908,023	3,001,457
20% extra inventory	1,325,200	5,523,165	3,178,157
30% extra inventory	1,223,520	6,196,018	3,218,545
40% extra inventory	1,251,530	6,969,590	3,328,714
Backup supplier	1,738,029	4,635,292	2,733,999
Small-scale disruption (one disrupted supplier)			
Disrupted	1,330,485	4,391,880	3,046,927
10% extra inventory	1,071,905	4,785,232	3,404,714
20% extra inventory	1,007,328	5,397,232	3,529,068
30% extra inventory	872,299	6,119,186	3,561,191
40% extra inventory	724,218	6,691,719	3,669,887
Backup supplier	1,167,796	4,338,754	3,339,046

4.6. Conclusions

The BSCs are susceptible to various disruptions, including those stemming from natural disasters, transportation challenges, and market fluctuations. Managing these disruptions is imperative to ensure the reliability and ongoing operations of bioenergy production. By identifying potential disruptions, developing mitigation strategies, and computing SCR, stakeholders can better prepare for and respond to adverse events. Resilience is a multifaceted

concept, and measuring only one aspect and generalizing it to overall SCR could lead to biased results. To address this issue, the current study developed a framework relying on the ABS to systematically quantify disruption and assess their propagation effects across multiple echelons of the SCN while incorporating mitigation strategies. Specifically, backup inventory and backup supplier strategies were implemented to evaluate their influence on restoring the operations at bio-hubs, which serve as critical nodes within the BSC. Six unique metrics, grounded in three resilience capacities supplemented by three structural indicators, were calculated to quantify SCR. Additionally, a detailed comparative analysis of the electricity generation outputs and cost profiles across several scenarios was conducted to evaluate the viability of each strategy. These metrics collectively offer valuable insights into the resilience of the BSCs and enable DMs to make informed decisions regarding the implementation of such strategies. The findings demonstrated the efficacy of both approaches, with backup inventory showing superior performance. This strategy resulted in a reduction of disruption propagation severity at bio-hubs, improved responsiveness, and increased the share of bioenergy within communities, albeit at a higher cost. However, it is important to note that in critical SCs, such as medical supplies, even slight improvements in resilience are crucial. In the case of remote communities, where biomass serves as the primary energy source, feedstock shortage due to unexpected events can result in significant reliability challenges, leaving communities without power for prolonged periods. Therefore, prioritizing resilience enhancements, even if they come at an added expense, is imperative.

For future research endeavors, scholars can adopt a simulation-based optimization approach to find the optimal value of decision variables, such as the inventory level of bio-hubs under disruption scenarios considering mitigation strategies. Moreover, the proposed agent-based model can be developed as a multi-objective model to evaluate other aspects, such as CO₂ emission under different scenarios. Additionally, as the value of structural metrics are highly dependent on the number of nodes and links, it is recommended to apply the proposed approach in large-scale networks to quantify the resilience of intricate network configurations. Furthermore, other resilience strategies, such as considering multiple transportation routes in the network and selecting suppliers based on risk criteria rather than purely cost, can be considered.

Chapter 5: An Adaptive Simulation-based Inventory Optimization Approach to Enhancing Biomass Supply Chain Resilience: A Case Study of Remote Communities

5.1. Introduction

As the global energy sector transitions from fossil fuels to renewable energy sources, the supporting supply chains (SCs) should evolve accordingly (Gital and Bilgen, 2024). Energy SCs, which facilitate production, transportation, and distribution of energy resources, are increasingly affected by market volatility, geopolitical instability, and climate-induced disruptions. These challenges highlight the need for SC configurations that can dynamically adjust to changing conditions and ensure energy security and operational continuity (Huang et al., 2024). This adaptability is particularly important in biomass supply chains (BSCs), where the interplay between resilience and sustainability determines long-term viability. A resilient BSC ensures consistent energy availability despite disruptions (e.g., supply, transportation and, demand), while a sustainable BSC minimizes environmental impacts (Rajabzadeh and Wiens, 2024). The growing attention to sustainable energy resources and environmental conservation has directed research toward developing BSCs, known for their renewable feedstocks and eco-friendly characteristics (Bahmani et al., 2024). Biomass feedstocks, derived from organic materials (e.g., agricultural and forestry residues), are plentiful and readily accessible natural resources for a more sustainable alternative to finite fossil fuels. These resources can be converted into several renewable energy forms, such as biogas, bioethanol, biodiesel, or electricity, through various conversion processes (Mafakheri et al., 2021).

Effectively managing the transition to bioenergy requires decision-making approaches that account for the distinct characteristics of these energy sources. Fossil fuels offer stability in supply but contribute to environmental degradation and higher costs, while biomass presents a renewable alternative but introduces variability in feedstock availability and logistics (Habibi et al., 2023a). Balancing resilience and sustainability objectives requires robust decision-making tactics that can account for stochastic variables and interconnected operational decisions. Central to this is inventory management, which directly influences the stability and efficiency of SC networks (Valipour et al., 2024). Effective strategies, such as adaptive monitoring intervals, are essential in managing feedstock availability and mitigating the risks of supply shortages (Ivanov et al., 2021). A well-integrated approach to energy supply chain management should enhance the adaptability of biomass sourcing and ensure a seamless transition that maintains reliability and cost efficiency in the face of uncertainty. Despite its

critical importance, inventory management in BSCs remains relatively underexplored in the literature (Valipour et al., 2024; Gital and Bilgen, 2024; Jazinaninejad et al., 2022). This gap is particularly evident in multi-echelon networks, where biomass is integrated into their energy mix, either as a standalone source or in conjunction with backup energy sources. Such environments introduce a unique set of challenges, such as i) coordinating inventory and replenishment decisions across multiple echelons with geographically distributed facilities that each have limited storage capacity, ii) accounting for the stochastic nature of biomass quality and transportation delays caused by seasonal or geographic constraints, and iii) dynamically switching between biomass and backup energy sources under system constraints, while ensuring operational reliability and reducing environmental emissions. Considering these important features, this study seeks to address three main research questions:

- 1) How can multi-echelon BSCs be coordinated to ensure reliable operations despite uncertainty, capacity limitations, and logistical constraints?
- 2) How can interdependencies across supply, processing, and distribution entities be modeled to capture system variability and enable adaptive decision-making?
- 3) How does addressing these challenges influence the sustainability and supply continuity of biomass-integrated energy networks?

To answer these questions, this research aims to develop a simulation-driven decision-support framework (DSF) for coordinating a multi-echelon BSC network, including suppliers, bio-hubs, and energy conversion facilities serving local communities, each constrained by limited storage capacities. Specifically, bio-hubs function as wood pellet production units, where raw feedstock is preprocessed into pellets to reduce perishability impact and enable storage for downstream distribution. This network operates under a dual sourcing configuration, with biomass as the primary feedstock. Diesel is used as a backup energy measure, which, despite its higher cost and environmental impact, ensures the continuity of energy generation during biomass shortages or when biomass marginal costs exceed diesel. Accordingly, the DSF adopts a bi-level inventory policy to systematically make replenishment decisions across bio-hubs and communities, while accounting for stochastic variations in feedstock quality, machine breakdown, and logistic delays. To capture these nonlinear dynamics and inter-tier feedback loops inherent in the network, the proposed DSF integrates agent-based simulation (ABS) and discrete event simulation (DES). This hybrid approach models the complex interactions, interdependencies, and temporal behaviors across SC tiers. Subsequently, metaheuristic algorithms are employed to derive inventory and sourcing policies under defined constraints, with the objective of minimizing coordination costs and accounting for the environmental impact of replenishment decisions. The framework directs the search process by iteratively generating candidate solutions and assessing their performance within the simulation model.

Leveraging feedback from multiple replications, solution quality is progressively refined based on performance metrics. A case study of remote off-grid communities in northern Quebec is examined to demonstrate the practicality of the proposed DSF.

The remainder of this study is organized as follows. Sections 5.2 and 5.3 describe the problem under study and introduce the basic concepts of simulation modeling, respectively. Section 5.4 provides a detailed explanation of the proposed DSF and developed modules. Section 5.5 presents an in-depth discussion of the results, including a sensitivity analysis of parameters that affect the outputs. Finally, Section 5.6 explores the theoretical, managerial, and practical implications of the research, and Section 5.7 concludes the study with final remarks and recommendations for future research.

5.2. Problem Statement

SCs today are increasingly exposed to a volatile market and supply conditions, tight capacity constraints, and complex interdependencies across multiple echelons (do Amaral et al., 2022). Accounting for such uncertainty and interdependence is especially critical in energy SCs, where disruptions can compromise energy delivery, reliability, and operational continuity. Conventional approaches typically struggle to capture dynamic behaviors, such as the nonlinear relationship between order size, processing time, and demand fulfillment across interconnected tiers. These models often do not consider the dynamic interplay across SC tiers and fail to capture how decisions in one tier can cascade through the network and undermine overall system performance over time (Ivanov et al., 2021; Vieira et al., 2023). Moreover, they often rely on simplifying assumptions, such as normally distributed demand and lead times (Darmawan, 2024), which are unrealistic, specifically in BSCs where supply is influenced by weather, harvest cycles, and supplier variability. Additionally, such approaches often face significant limitations due to the exponential growth of the solution space as the number of risk factors increases. This growth restricts their practical applicability and makes the models computationally expensive to solve within reasonable timeframes (Chen et al., 2024). This phenomenon, which is referred to as the “curse of dimensionality”, highlights the need for advanced DSFs that can accommodate real-world uncertainties and model dynamic interactions across tiers, while maintaining both solution quality and computational feasibility (De Kok et al., 2018).

To overcome these challenges, this study proposes an adaptive simulation-driven DSF that integrates ABS, DES, and a metaheuristic optimization algorithm to construct a high-fidelity digital representation of a BSC network. The overall objective is to minimize the total system cost while deriving replenishment strategies for the midstream and downstream echelons based on inventory control policies under a stochastic environment. System

performance is assessed through key performance indicators (KPIs), including generated bioenergy (GW), unmet bioenergy demand (compensated by diesel) (GW), total cost (\$), and environmental impact in terms of CO₂ emissions from transportation and electricity generation (Kg CO₂ eq.). This framework leverages the capability of simulation techniques, which often surpass traditional algebraic models in capturing the behavior of complex systems. Unlike conventional models that rely on fixed equations and static relationships, simulations can dynamically represent the intricate mechanisms and interactions within a system (Ivanov and Dolgui, 2019). By embedding optimization within the simulation environment, the DSF captures system variability while systematically searching for near-optimal strategies. This integration ensures that decision-making goes beyond descriptive insights and provides prescriptive guidance for managing BSCs under uncertainty over varying time frames.

5.2.1. Case Study Description

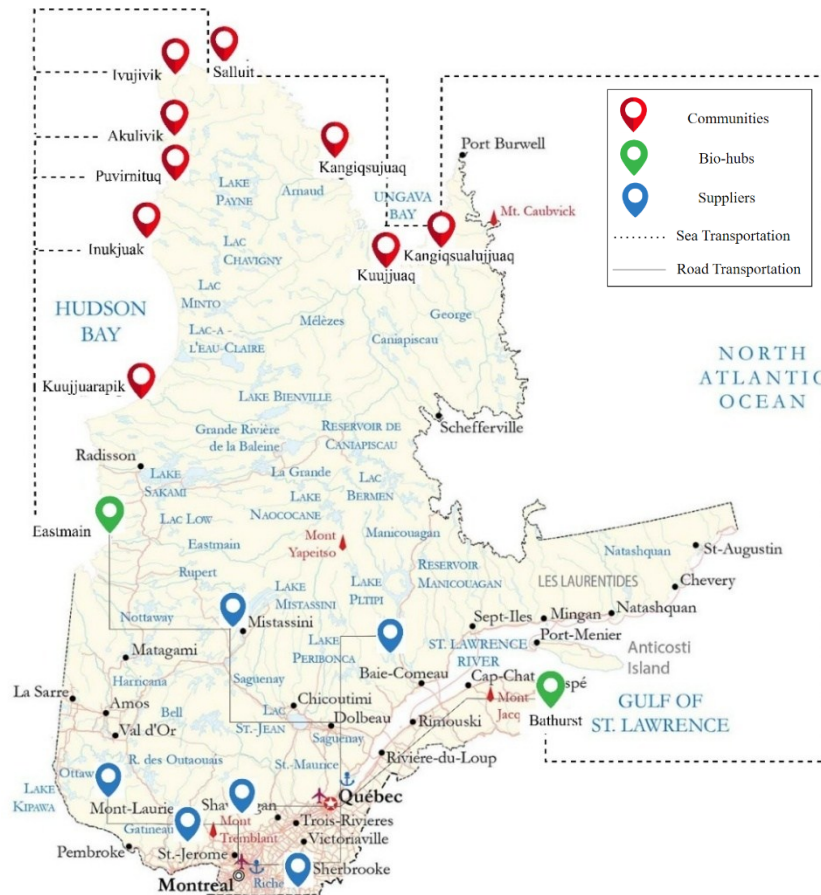
This study considers nine remote, off-grid Inuit communities of Kangiqsujaq, Salluit, Ivujivik, Kuujuaq, Inukjuak, Puvirnituk, Kangiqsualujuaq, Akulivik, and Kuujjuarapik in Quebec's Nunavik region as representative case studies to quantify the challenges and opportunities of implementing a BSC network in isolated northern regions using the proposed DSF. The geographical positioning of these communities presents a distinctive logistical challenge, as their sole access is through waterways of the Hudson Bay and the Labrador Sea. These remote communities, which are off-grid as well, rely on diesel-fired generation for electricity needs. The high operating costs of diesel fuel, coupled with the high air pollution from combustion relative to other types of generation and its price volatility, emphasize the necessity for more secure and clean energy resources (CER, 2018b). Due to such difficulties, many remote communities in Canada are looking for ways to decrease their dependence on diesel fuel, enhance the reliability of their electricity supply, and lower carbon emissions (CER, 2024). Therefore, switching to a local renewable energy source, which is cleaner, less susceptible to fluctuations in energy prices, and storable in different forms can benefit them in terms of energy security.

Among the renewable energy technologies explored and tested in Arctic and sub-Arctic climates, bioenergy has demonstrated significant potential (Moreno et al., 2024). Hence, a BSC network consisting of biomass suppliers, bio-hubs, and communities is proposed in this case study. Communities are responsible for electricity generation from biomass and storing feedstock in local facilities to meet short-term needs. However, in the event of unexpected disruptions (e.g., supply shortages), diesel is used as a mitigation measure to ensure an uninterrupted power supply. Transportation availability is further constrained by seasonal conditions, as waterways, the sole transportation route, are accessible only when ice-free.

Therefore, any delay in feedstock delivery can considerably disrupt bioenergy production. Two bio-hubs are considered in this network, each representing an individual pathway supplied by participant suppliers (Mafakheri et al., 2021). Therefore, by centralizing community needs at bio-hubs, supply scalability and ordering efficiency are enhanced while addressing the challenges posed by geographic dispersion and distance. Due to the logistical and handling challenges associated with biomass, particularly highly moisturized feedstock like forestry biomass, there is a significant risk of biomass losses, reduced heating value (HV), and the proliferation of fungal spores during prolonged storage (Routa et al., 2018). To address these challenges, wood pellet production technology is used in the hubs. Wood pellets have uniform physical and chemical properties, so communities receive high-quality and consistent feedstock. Figure 5.1 provides a visual representation of the studied BSC network, including the locations of the communities, two bio-hubs, and biomass suppliers, to better illustrate the geographic dispersion and logistical complexity of the region. The map displays approximate maritime and overland transportation routes to provide a general overview of regional connectivity. While these routes are illustrative, the precise transportation pathways are determined through OpenStreetMap during model implementation to ensure spatial accuracy.

5.3. Preliminaries

The literature identifies four primary simulation approaches for modeling SCs: Monte Carlo, SD, DES, and ABS. Monte Carlo and SD rely on mathematical equations to build their models, whereas DES and ABS depend on computer code implementations and behavioural logics (Saisridhar et al., 2024). ABS focuses on the interactions of autonomous agents within the system, which makes it particularly powerful at addressing complexities arising from external stressors and various uncertainty sources (Habibi et al., 2023a). DES, on the other hand, is appropriate for modeling systems with well-defined processes, as it primarily models the flow of entities through the discrete events that impact their trajectories. Importantly, compared to Monte Carlo and SD, which provide more aggregated and equation-based representations, ABS and DES enable richer behavioral detail, adaptive responses, and a closer alignment with real-world operational complexities (Saisridhar et al., 2024).



As a bottom-up modeling approach, simulation derives system-level behavior from the aggregated actions and interactions of its components. An ABS typically comprises agents, their relationships, and the environment in which they operate (Seçkiner and Koç, 2022). Agents represent entities, such as suppliers, vehicles, or facilities, and are assigned attributes and behavioral rules that govern their responses to environmental changes and interactions with other agents. This modular structure allows each SC component to execute context-specific tasks (e.g., procurement, production, inventory management, and transportation) according to predefined policies. This, in turn, enables a detailed and adaptive representation of complex, decentralized operations (Sun et al., 2022). Moreover, simulation models provide the capability of evaluating real-time operations, accounting for dynamic interactions among SC components, and incorporating stochastic variations in inputs and processes, thereby offering a realistic representation of system behavior and actionable insights (Vieira et al., 2023).

5.4. Proposed DSF

To bridge the existing knowledge gap in inventory planning for BSCs, this study develops a DSF that integrates simulation with optimization techniques. This integration is particularly advantageous in complex stochastic environments, where deriving closed-form objective functions is computationally infeasible or analytically intractable, and evaluating each solution requires dynamic evaluation due to path-dependent and probabilistic system behaviors. In pure simulation, uncertain parameters and potential input combinations to be explored are typically treated as fixed inputs or varied within predefined ranges to assess KPIs. However, evaluating each scenario manually is not feasible due to the vast number of potential combinations (Seçkiner and Koç et al., 2022). Therefore, the proposed framework enables robust decision-making under uncertainty by combining simulation's ability to model system behavior with optimization's capacity to navigate large decision spaces. The key phases in developing this DSF are illustrated in Figure 5.2 and are detailed in this section.

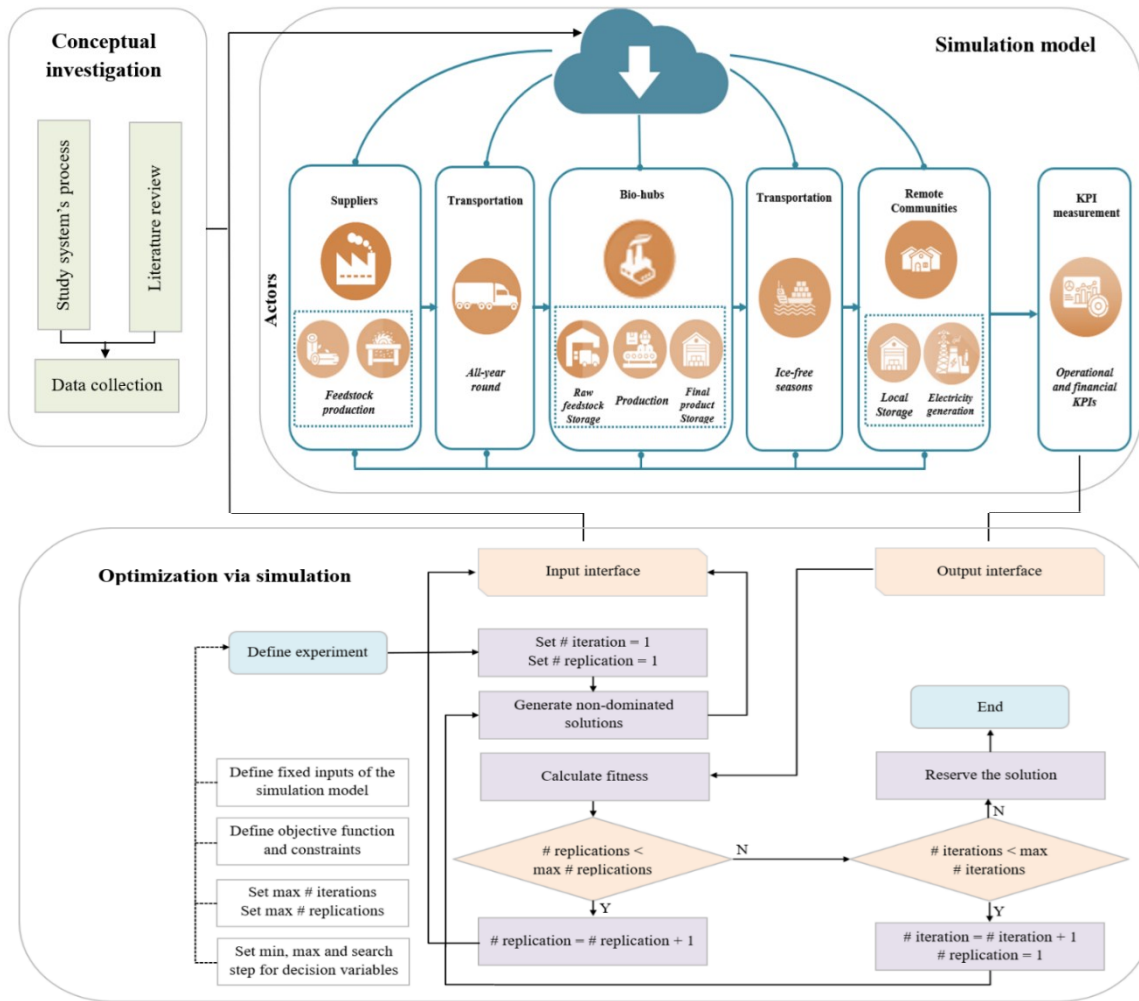


Figure 5.2. The implementation phases of the proposed DSF

5.4.1. Implementation Phases of the Proposed DSF

The initial phase of developing the framework is conducting a comprehensive conceptual analysis of the system's structure and key interactions. In the next phase, the interdependencies among BSC components are systematically modeled through agent-based rules, while the dynamics of material flow and pellet production processes within bio-hub are captured using DES. The inventory replenishment strategies are established based on (s, S) inventory control policy. The temporal initiation of replenishment is predicated on s , and an ordering action is activated upon the depletion of inventory below a predefined threshold of S . Accordingly, the replenishment quantity is computed as the differential between S and the current inventory (Ivanov et al., 2021). In addition to constraints related to inventory balance, transportation time, storage, and production limitations defined within the simulation model, it is also essential to establish the condition $s \leq S$ for each node in the optimization layer. This constraint guarantees that the reorder point remains consistently below the target level to mitigate the risk of stockouts and optimize resource allocation across all echelons. Notably, the (s, S) inventory policy emerges as the most appropriate choice considering the perishable nature of the feedstock, as supported by the literature (Akhtari et al., 2019; Nguyen and Chen, 2022). The simulation modeling rules are illustrated in Figure 5.3 and detailed in section 5.5.2 to offer a thorough overview of the agents involved and the specific actions they undertake. To enhance the clarity of the proposed DSF, Table 5.1 provides a structured summary of the key input parameters, and state variables employed in the study. While the DSF is not based on conventional mathematical models and much of the model's logic is embedded in code, this table is intended to improve traceability and promote transparency to support future replication and methodological rigor.

The final phase of the proposed DSF aims to find near-optimal solutions in a simulated environment, while minimizing cost and meeting specific constraints. As shown in Figure 5.2, the process involves an iterative loop: the optimization layer generates a set of candidate solutions, and the simulation layer evaluates these candidates to determine their performance. In this context, the inventory configurations (s, S) are treated as decision variables within the optimization layer, while metaheuristics generating candidate solutions and feedback loops iteratively refining the search to progressively converge toward high-quality solutions (see Figure 5.2). This iterative process continues until the optimization algorithm converges on a solution that meets the desired criteria or objective. Notably, within each replication of a given iteration, stochastic values for uncertain parameters are generated using Monte Carlo

simulation. This approach enables the model to incorporate system variability and evaluate the robustness of candidate solutions under uncertainty, which provides insights that a single simulation run cannot offer.

In this study, the genetic algorithm (GA) is integrated with the developed simulation model to identify the parameter settings while minimizing total cost. Inspired by natural selection principles, the GA iteratively refines potential solutions by computing the fitness function through a simulation model and evaluating them against the defined KPIs. This algorithm maintains population diversity in the solutions through crossover and mutation and consequently reduces the risk of premature convergence, which is a challenge in problems with high levels of stochasticity (Papazoglou and Biskas, 2023). Compared to other classical metaheuristics such as particle swarm optimization, simulated annealing, tabu search (TS), and scatter search (SS), the search mechanism of GA has made it powerful in exploring multimodal search spaces and prevents premature convergence. Moreover, GA's parallelism facilitates faster convergence in complex, non-linear problems (Osaba et al., 2021).

Table 5.1. The nomenclature used in formulating the studied problem

k	Set of candidate suppliers ($k = 1, 2, \dots, K$)	
i	Set of candidate bio-hubs ($i = 1, 2, \dots, n$)	
j	Set of candidate communities ($j = 1, 2, \dots, m$)	
c	Set of machines used within bio-hubs ($c = 1, 2, \dots, C$)	
t	Set of time periods ($t = 1, 2, \dots, T$)	
Inputs		
<i>Supplier:</i>		
	Location of supplier k	
	Maximum production capacity of supplier k	tonne
	Working shifts of supplier k	h
	Feedstock MC of supplier k	%
	Feedstock HV of supplier k	GJ/dried tonne
	Biomass delivery cost from supplier k to bio-hub i	\$/dried tonne
<i>Bio-hub:</i>		
	Location of bio-hub i	
	Maximum storage capacity of bio-hub i	tonne
	Burner heat demand	kWh/tonne _{ev.w.}
	Power of machine c	kWh
	Capacity of machine c	tonne.h
	Burner efficiency	%
	Simultaneity factor of machine c	%
	Time between failure machine c	h
	Time to repair machine c	h
	Target MC	%
	Working shifts of bio-hub i	h
	Biomass delivery cost from bio-hub i to community j	\$, tonne
	Holding cost of raw feedstock at bio-hub i per unit of time	\$, tonne
	Holding cost of wood pellet at bio-hub i per unit of time	\$, tonne
	Electricity price	\$/kWh

Table 5.1 (Continued)

Inputs	
<i>Community:</i>	
Location of community j	
Maximum local storage capacity at community j	tonne
Levelised biomass-to-electricity conversion cost at community j	\$/kWh
Levelised electricity generation cost from diesel (alternative fuel)	\$/kWh
Holding cost of wood pellet at community per unit of time	\$/tonne
Projected electricity demand of community j	kWh
Biomass-to-electricity conversion rate at community j	kWh/kg
Loading factor of electricity generation from biomass at community j	-
Capacity of electricity generation from biomass at community j	kW
<i>Transportation:</i>	
Biomass delivery time window from supplier k to bio-hub i	Month
Biomass delivery time window from bio-hub i to community j	Month
Truck Capacity	tonne
Ship Capacity	tonne
Truck speed	Km/h
Ship speed	Km/h
Truck loading and unloading time	Minute
Ship loading and unloading time	Minute
Truck transportation operating hours	h
Truck fuel consumption rate	lit/km
Truck CO ₂ emission rate	kg/lit
Ship fuel consumption rate	g/tonne km
Ship CO ₂ emission rate	kg/lit
State Variables	
Amount of feedstock delivered to bio-hub i by supplier k at t	tonne
Production amount of supplier k at t	tonne
Order received by supplier k at t	tonne
On-hand inventory amount at bio-hub i at t	tonne
Order registered amount by bio-hub i at t	tonne
Order received by bio-hub i at t	tonne
Amount of wood pellet delivered to community j by bio-hub i at t	tonne
Amount of feedstock used in burner	tonne
Electricity consumption of machine c at t	kW
Order registered amount by community j at t	tonne
On-hand inventory amount at community j at t	tonne
Electricity generated from biomass at community j at t	kWh
Electricity generated from diesel at community j at t	kWh
Biomass used for electricity generation at community j at t	tonne
CO ₂ emissions of truck	Kg CO ₂ eq.
CO ₂ emissions of ship	Kg CO ₂ eq.
CO ₂ emissions of biomass combustion	Kg CO ₂ eq.
CO ₂ emissions of diesel combustion	Kg CO ₂ eq.
Number of truckloads at t	-
Number of shiploads at t	-
Decision Variables	
S level of bio-hub i at t	tonne
s level of bio-hub i at t	tonne
S level of community j at t	tonne
s level of community j at t	tonne

5.4.2. BSC Network Simulation

This section details the behavioral rules of the proposed BSC network implemented within the simulation layer. Each module operates in a cyclic, event-driven manner, where discrete events trigger predefined actions such as data updates, decision-making, and inter-agent communication. Upon completing these actions, the module awaits the next event, which forms a continuous feedback loop that captures the dynamic, time-dependent behavior of BSC operations.

5.4.2.1. Supplier Module

Suppliers, which in our case are wood processing plants, are responsible for providing feedstock to bio-hubs. Operating within a structured timeframe of five days per week and two shifts per day (each shift lasting 8 hours), suppliers produce sawdust as a by-product. The feedstock quality is assessed based on moisture content (MC) represented by the Weibull (3.39, 9.02) + 21 distribution and HV modeled using Normal (18, 0.3) distribution (Mobini et al., 2013). Accordingly, suppliers are paid based on the dried weight of the delivered raw material. As shown in Figure 5.3, this module coordinates the processing and dispatching of feedstock orders to bio-hubs while accounting for capacity and logistical constraints, such as truckload size limitations. To enhance transportation efficiency, the model enforces a policy against partial truckload shipments, ensuring trucks are dispatched only when fully loaded. The detailed behavior of this module is outlined in Algorithm 5.1.

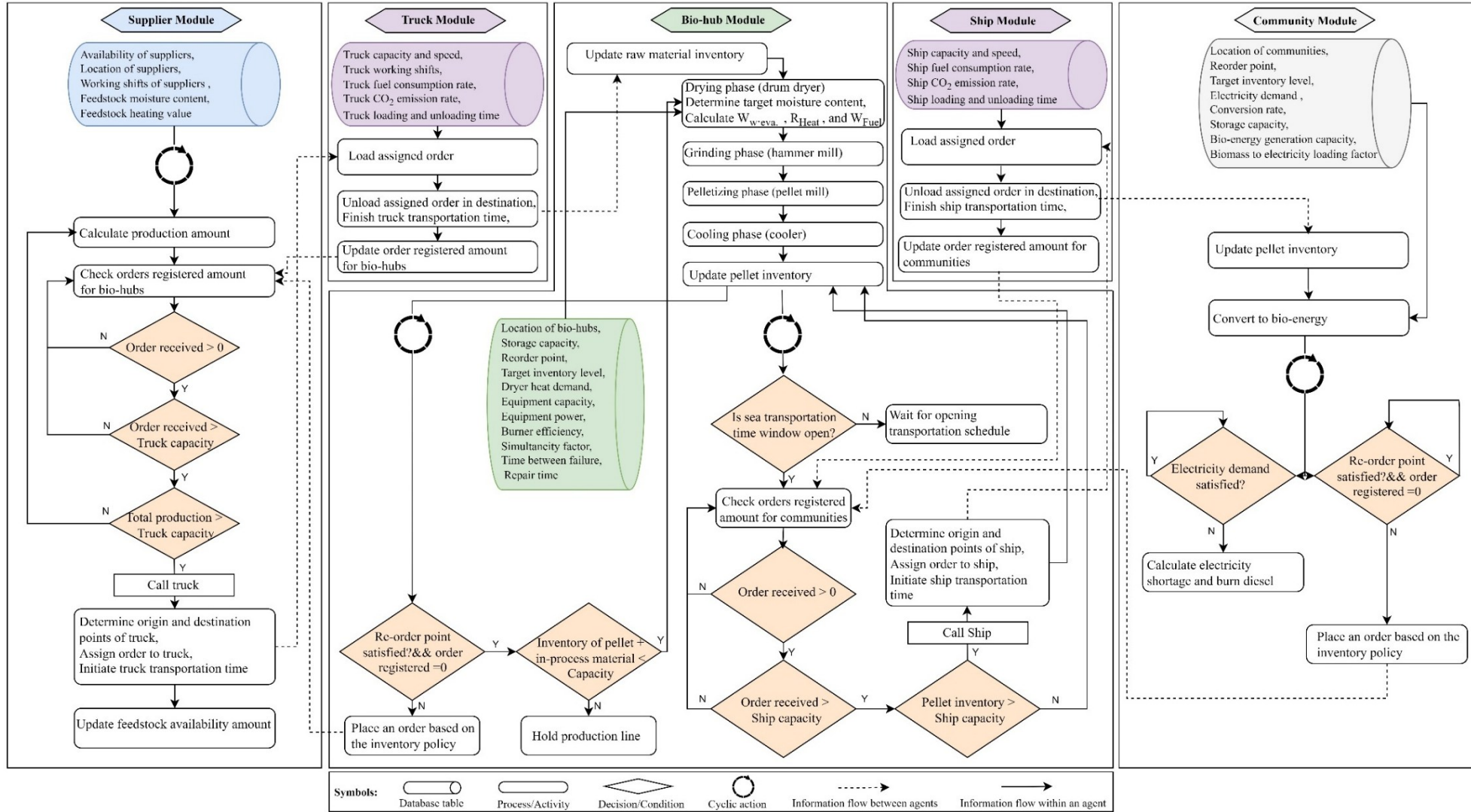


Figure 5.3. Simulation workflow for the proposed BSC and agents' interplay

Algorithm 5.1. Order processing in supplier module

Order Checking “event”

```
If (getHourOfDay() >= SupplierStartShift && getHourOfDay() <= SupplierFinishShift)
    If (orderReceivedAmount.size() > 0 && orderReceivedAmount.get(0) != 0)
        If (orderReceivedAmount.get(0) > main.biomassTransferAmountByTruck)
            If (totalProduction >= main.biomassTransferAmountByTruck)
                TotalProduction -= main.biomassTransferAmountByTruck;
                main.add_trucks();
                int which = main.trucks.size()-1;
                Determine the origin point of truck;
                Determine the destination point of truck;
                main.trucks.get(which).biomassAmount =
                main.biomassTransferAmountByTruck;
                main.trucks.get(which).moistureContent = moistureContent;
                main.trucks.get(which).heatingValue = heatingValue;
                OrderReceivedAmount.set(0, orderReceivedAmount.get(0)-
                main.biomassTransferAmountByTruck);
                Send “move” to truck agent;
                For bio-hub [i]  $\forall i \in \{1,2,\dots,n\}$ 
                    deliveredToHub[i] += main.trucks.get(which).biomassAmount;
                    leadTimeHub [i].add(time() - orderReceivedTime.get(0));
                    If (OrderReceivedAmount.get(0)==0)
                        OrderReceivedAmount.remove(0);
                        OrderReceivedHub.remove(0);
                        OrderReceivedTime.remove(0);
```

End

5.4.2.2. Bio-Hub Module

In this study, bio-hub module is equipped with a wood pellet production line that integrates multiple processes to ensure efficient transformation of raw biomass into high-quality wood pellets. The production begins with the drying phase, where the MC of the biomass feedstock is lowered to a target level to achieve ideal conditions for the subsequent pelletization process. This process is important for maximizing the quality of the pellets, as MC directly influences material's compressibility and durability of final pellets. The detailed description of this phase, along with the subsequent processes, shown in Figure 5.3, and corresponding equations is provided to offer a comprehensive understanding of the technical foundations of pellet production.

I) *Drying process*: The aim of this process is to facilitate moisture removal from the raw feedstock while maintaining a consistent input rate as long as raw materials are available. Fluctuations in MC are controlled by adjusting the fuel feed rate into the burner, where biomass combustion generates the required heat for drying. In this case, the amount of biomass needed for a given time interval is calculated using Equation (5.1).

$$W_{\text{Fuel}} = \frac{R_{\text{Heat}}}{HV_{\text{Fuel}} * (1 - MC_{\text{Fuel}}) * \theta} \quad (5.1)$$

Where, W_{Fuel} denotes the required mass of the fuel (*tonne*), HV_{Fuel} represents the HV of the fuel (kWh/*tonne*), MC_{Fuel} indicates the MC of the fuel, and θ stands for the efficiency of the burner (%). In this equation, R_{Heat} quantifies the thermal energy required to reach the specified level of moisture reduction. This parameter is determined by the volume of water that must be evaporated ($W_{\text{w.eva.}}$), which is directly affected by both the initial and target MC of the material. Additionally, the heat demand of the dryer (HDD), specified by the manufacturers, must be established to calculate $W_{\text{w.eva.}}$. This value is essential for calculating the energy requirements of the drying process (Oberberger and Thek, 2010). Equations (5.2) and (5.3) formulate R_{Heat} and $W_{\text{w.eva.}}$ respectively.

$$R_{\text{Heat}} = W_{\text{w.eva.}} * HDD \quad (5.2)$$

$$W_{\text{w.eva.}} = W_{\text{wet}} - \frac{dW_{\text{wet}}}{1 - MC_t} \quad (5.3)$$

Wherein, W_{wet} and dW_{wet} represents the initial wet weight (*tonne*) and dried weight of feedstock (*tonne*) fed into the dryer, while MC_t denotes the target MC, which serves as an input for the simulation.

II) *Size reduction (grinding), pelletizing, and cooling*: Size reduction, typically carried out using hammer mills reduces the particle size of raw materials to enhance their suitability for pelletization. Subsequently, pellet mills convert the finely ground materials into uniform pellets and enhance their density and combustion properties. After pelletization, the cooling phase is executed using counterflow coolers, a commonly used technology in the pellet production industry, to reduce the temperature of the newly formed pellets. Table 5.2 presents key inputs for modeling the pellet production line, including the operational parameters of the required machinery (Mobini et al., 2013).

Table 5.2. Pellet production machines' data (working 24 h every day)

	Drum dryer	Hammer mill	Pellet mill	Cooler
Heat demand (kWh/ <i>tonne_{ev.w.}</i>)	1300	-	-	-
Capacity (<i>tonne/h</i>)	25	10	5	10
Power (kWh)	270	370	300	25
Fuel	Wet sawdust	-	-	-
Burner efficiency (%)	U (50-60)	-	-	-
Simultaneity factor (%)	U (85-100)	U (85-100)	U (85-100)	U (85-100)
Time between failure (h)	Exp (25)	Exp (15)	Exp (10)	Exp (30)
Time to repair (h)	Exp (1)	Exp (0.5)	Exp (1)	Exp (0.5)

As illustrated in Figure 5.3, beyond pellet production, bio-hubs manage raw feedstock processing, handle wood pellet storage, and serve as coordination points to facilitate seamless order information exchange between supplier and remote community modules. Bio-hubs are designed with a dual-purpose storage configuration, featuring a yard for raw materials and a depot for finished wood pellets storage with the storage cost of 2 \$ per unit of time (Mafakheri et al., 2021). After verifying community orders, the order processing phase initiates through a cyclic “event” in alignment with the (s, S) policy. It subsequently determines order quantities and executes a supplier selection process, in which suppliers are ranked according to their availability and cost, respectively. It should be mentioned that a “queue” is considered within the production line to hold production process whenever the capacity is full to apply the capacity constraint of bio-hubs regarding final product storage. Algorithm 5.2 outlines the inventory and order processing events, which systematically monitor on-hand and in-process inventory, track biomass in transit, update incoming orders from downstream echelons, assign shipment loads, and ensure storage and production capacities are not exceeded. These operations incur various costs, such as storage costs of raw materials and wood pellets, purchasing expenses, and electricity costs associated with production line operations, all contributing to the total module cost. The electricity cost is calculated based on the electricity consumption amount during the production process and the simultaneity factor (%), which adjusts the equipment’s power consumption based on its nominal power and current operating conditions (Oberberger and Thek, 2010).

Algorithm 5.2. Operations interplay within bio-hub module

5.2.1. Inventory Checking “event”

```
For bio-hub [i]  $\forall i \in \{1, 2, \dots, n\}$ 
  If bio-hub [i] is active==1
    If (((inventory + buffer2.size() + buffer3.size() + buffer4.size() +
    drumDryer.queueSize() + drumDryer.delaySize() +
    hammerMill.queueSize() + hammerMill.delaySize() +
    pelletMill.queueSize() + pelletMill.delaySize() + cooler.queueSize() +
    cooler.delaySize()) < main.sLevelHub[i]) && orderRegistered == 0)
      double amount = main.SSLevelHub[i] - (inventory + buffer2.size() +
      buffer3.size() + buffer4.size() + drumDryer.queueSize() +
      drumDryer.delaySize() + hammerMill.queueSize() +
      hammerMill.delaySize() + pelletMill.queueSize() + pelletMill.delaySize() +
      cooler.queueSize() + cooler.delaySize());
      amount = amount;
      int temp = (int) amount;
      temp = temp;
      orderRegistered = temp;
      ordering (amount);
```

End

5.2.2. Ordering “function”

```
For (int ii=0; ii<main.suppliers.size(); ii++)
  If (main.suppliers.get(ii).totalProduction > amount)
    temp.add(ii);
    If (temp.size() > 0)
      double minPrice = main.suppliers.get(temp.get(0)).price;
      int which = temp.get(0);
    For (int jj=1; jj<temp.size(); jj++)
      If (main.suppliers.get(temp.get(jj)).price < minPrice)
        which = temp.get(jj);
        minPrice = main.suppliers.get(jj).price;
        main.suppliers.get(which).orderReceivedAmount.add(amount);
        main.suppliers.get(which).orderReceivedHub.add(this.getIndex());
        main.suppliers.get(which).orderReceivedTime.add(time());
        biomassPurchasingCost += main.suppliers.get(which).price * amount * (1-
        main.suppliers.get(which).moistureContent);
      Else int numberOfOrdering = (int) (amount /
      main.biomassTransferAmountByTruck);
      For (int ii=0; ii<numberOfOrdering; ii++)
        int which = uniform_discr(0, main.suppliers.size()-1);
        main.suppliers.get(which).orderReceivedAmount.add
        (main.biomassTransferAmountByTruck);
        main.suppliers.get(which).orderReceivedHub.add(this.getIndex());
        main.suppliers.get(which).orderReceivedTime.add(time());
        biomassPurchasingCost += main.suppliers.get(which).price *
        main.biomassTransferAmountByTruck *
        (1- main.suppliers.get(which).moistureContent);
        totalCost += main.suppliers.get(which).price *
        main.biomassTransferAmountByTruck *
        (1-main.suppliers.get(which).moistureContent);
      If (this.getIndex() == 0)
        temp.clear();
```

End

Algorithm 5.2 (Continued)

5.2.3. Order Processing “event”

```
For bio-hub [i]  $\forall i \in \{1, 2, \dots, n\}$ 
  If bio-hub [i] is active==1
    If (getHourOfDay() >= main.bioHubtStartShift && getHourOfDay() <=
      main.bioHubFinishShift)
      If (orderFromCommunityAmount.size() > 0)
        For (int ii=0; ii<orderFromCommunityAmount.size(); ii++)
          If (orderFromCommunityAmount.get(ii) == 0)
            orderFromCommunityAmount.remove(ii);
            orderFromCommunityID.remove(ii);
            orderFromCommunityTime.remove(ii);
            ii--;
          If (getMonth() >= main.bioHubToCommunityMonthStart &&
            getMonth() <= main.bioHubToCommunityMonthFinish)
            If (orderFromCommunityAmount.size() > 0)
              If (orderFromCommunityAmount.get(0) >
                main.biomassTransferAmountByShip)
                If (inventory >
                  main.biomassTransferAmountByShip)
                  main.add ships();
                  int which = main.ships.size()-1;
                  Determine the origin point of ship;
                  Determine the destination point of ship;
                  main.ships.get(which).orderTime =
                    orderFromCommunityTime.get(0);
                  orderFromCommunityAmount.set(0,
                    orderFromCommunityAmount.get(0) -
                    main.biomassTransferAmountByShip);
                    main.ships.get(which).biomassAmount =
                    main.biomassTransferAmountByShip;
                    Send “move” to ship agent;
                    For community [j]  $\forall j \in \{1, 2, \dots, m\}$ 
                      deliveredTocommunity[j] +=
                        main.ships.get(which).biomassAmount;
                      If (orderFromCommunityAmount.get(0) == 0)
                        orderFromCommunityAmount.remove(0);
                        orderFromCommunityID.remove(0);
                        orderFromCommunityTime.remove(0);
                        inventory -= main.biomassTransferAmountByShip;
                    If (orderFromCommunityAmount.size() > 0)
                      For (int ii=0; ii<orderFromCommunityAmount.size(); ii++)
                        main.remoteCommunities.get(orderFromCommunityID.get(ii)).orderRegistered -=
                          orderFromCommunityAmount.get(ii);
                          totalOrderInHand -= orderFromCommunityAmount.get(ii);
                          orderFromCommunityAmount.clear();
                          orderFromCommunityID.clear();
                          orderFromCommunityTime.clear();
                          If ((inventory + buffer2.size() + buffer3.size() + buffer4.size() +
                            drumDryer.queueSize() + drumDryer.delaySize() +
                            hammerMill.queueSize() + hammerMill.delaySize() +
                            pelletMill.queueSize() + pelletMill.delaySize() +
                            cooler.queueSize() + cooler.delaySize()) < capacity)
                            hold.unblock();
```

End

Algorithm 5.2 (Continued)

5.2.4. Cost Updater “event”

```
For bio-hub [i]  $\forall i \in \{1, 2, \dots, n\}$ 
    ElectricityCost += uniform (0.85, 1) * main.priceOfElectricity*
    ((powerDryer* (capacityDryer/60))+ (powerHammerMill* (capacityHammerMill/60)) +
    (powerPelletMill*(capacityPelletMill/60)+ (powerCooler * (capacityCooler/60)))));
    InventoryCost += (holdingCost * inventory);
    InventoryRawCost += (holdingCostRawMaterial * totalRawWeight);
    TotalCost += (holdingCost * inventory) + (holdingCostRawMaterial * totalRawWeight) +
    ElectricityCost + biomassPurchasingCost;
    main.totalCostSupplyChain += TotalCost;

End
```

5.4.2.3. Remote Community Module

Communities are the final echelon of the proposed BSC tasked with electricity generation from either biomass or backup fuel (i.e., diesel) to fulfill their energy requirements (see Figure 5.3). To mitigate the logistical constraints and uncertainties associated with sea transportation, each community maintains a local reserve of biomass feedstock, with an associated storage cost of \$4 per unit of time (Mafakheri et al., 2021). Therefore, the total cost of communities includes costs for wood pellet storage and ordering/delivery costs, as well as generating electricity from biomass and diesel. To determine the last two cost components, the levelized generation cost (\$/kWh) is employed to facilitate the standardized comparison of alternative energy production technologies (Mafakheri et al., 2021). To put it precisely, the levelized cost of electricity represents the per-unit cost of electricity generation, derived by distributing the total costs of electricity generation, including capital investment and operation and maintenance costs over the facility’s operational lifetime. The ordering process is governed by the defined inventory policy to facilitate timely replenishment and efficient inventory management in response to fluctuations in operational dynamics. A systematic presentation of the interactions among components within this module, along with the related events and functions, such as energy generation, ordering processes, and community-level procurement, is provided in Algorithm 5.3.

Algorithm 5.3. Operations interplay within community module

5.3.1. Order Processing “event”

```
For Community [j]  $\forall j \in \{1, 2, \dots, m\}$   
    If (inventoryBiomass < main.sLevelCommunity[j] && orderRegistered == 0)  
        double amount = main.SSLevelCommunity[j] - inventoryBiomass;  
        amount = (int) amount;  
        orderRegistered += amount;  
        ordering (amount);  
End
```

5.3.2. Ordering “Function”

```
For bio-hub [i]  $\forall i \in \{1, 2, \dots, n\}$   
    If bio-hubs are located at equal geographical distances  
        Pick randomly;  
    Else Pick the nearest bio-hub  
        If ((main.biohubs.inventory - main.biohubs.totalOrderInHand) >  
            amount && main.biohubs.get(0).isActive == 1)  
            main.biohubs.orderFromCommunityAmount.add (amount);  
            main.biohubs.orderFromCommunityID.add(this.getIndex());  
            main.biohubs.orderFromCommunityTime.add(time());  
            main.biohubs.totalOrderInHand += amount;  
            For (this.getIndex[j] )  $\forall j \in \{1, 2, \dots, m\}$   
                costPurchasingBiomass += main.biohubs.pricec *  
                    amount;  
            totalCost += main.biohubs.pricec * amount;  
End
```

5.3.3. Electricity consumption calculation “Function”

```
counter++;  
totalElecDemand += electricityNeeded;  
double hourElecNeeded = electricityNeeded;  
double maxBiomassGeneration = elecGenCapacity * loadingFactor;  
double amount1 = min (maxBiomassGeneration, hourElecNeeded);  
double KgNeeded = min((amount1/biomassConversionrate)/loadingFactor , (inventoryBiomass *  
1000));  
amount1 = min (amount1, KgNeeded * biomassConversionrate * loadingFactor);  
If (KgNeeded == 0)  
    powerFromDiesel += hourElecNeeded;  
    totalCost += hourElecNeeded * dieselGenerationCost;  
    costDieselToElec += hourElecNeeded * dieselGenerationCost;  
    main.totalCostSupplyChain += hourElecNeeded * dieselGenerationCost;  
Else  
    If (amount1 == hourElecNeeded)  
        powerFromBiomass += amount1;  
        inventoryBiomass -= (KgNeeded / 1000);  
        biomassKGUsed += (KgNeeded / 1000);  
        totalCost += amount1 * biomassConversionCost;  
        costBiomassToElec += amount1 * biomassConversionCost;  
        main.totalCostSupplyChain += amount1 * biomassConversionCost;  
    Else double remainNeeded = hourElecNeeded - amount1;  
        powerFromDiesel += remainNeeded;  
        totalCost += remainNeeded * dieselGenerationCost;  
        costDieselToElec += remainNeeded * dieselGenerationCost;  
        main.totalCostSupplyChain += remainNeeded * dieselGenerationCost;  
        powerFromBiomass += amount1;  
        inventoryBiomass -= (KgNeeded / 1000);  
        biomassKGUsed += (KgNeeded / 1000);  
        totalCost += amount1 * biomassConversionCost;  
        costBiomassToElec += amount1 * biomassConversionCost;  
        main.totalCostSupplyChain += amount1 * biomassConversionCost;  
End
```

Figure 5.4 illustrates the hourly electricity demand profiles for nine off-grid communities, derived from the annual demand data (CER, 2018a) and average monthly trends reported by Hydro-Quebec (2023). The plots reveal distinct seasonal patterns, with marked winter peaks attributed to heating loads and reduced daylight hours, and comparatively lower summer demand. According to this figure, certain communities, such as Kuujjuaq experience sharper and more persistent winter demand, suggesting higher heating intensity and prolonged load stress. In addition to this information, Table 5.3 presents the input parameters for this module with a focus on operational factors relevant to electricity conversion technology (IRENA, 2018; NEB, 2017; Mafakheri et al., 2021).

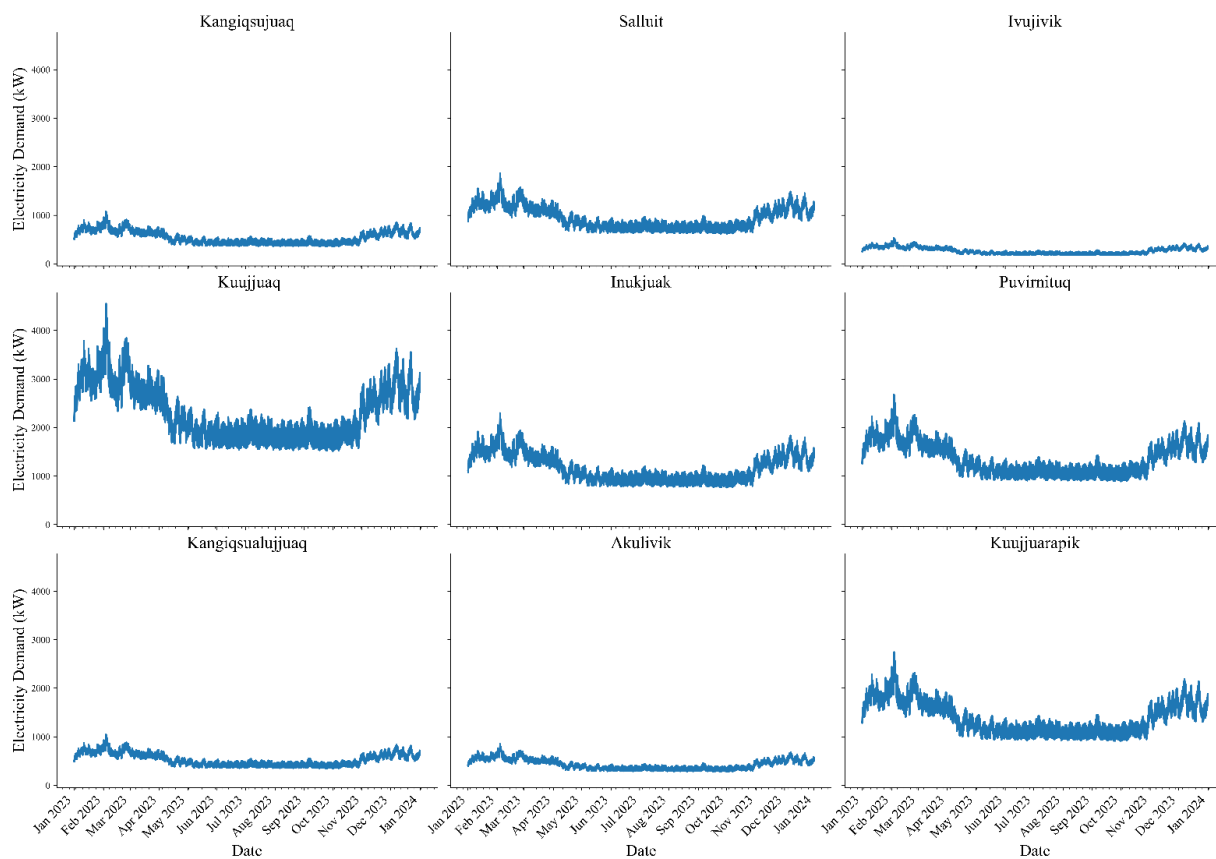


Figure 5.4. Hourly electricity consumption in communities in the year 2023

Table 5.3. The input parameters of remote community module

Parameter	Value
Biomass-to-electricity conversion rate (kWh/kg)	4.7
Capacity of electricity generation from biomass (kW)	6000
Loading factor of electricity generation from biomass	0.8
Levelised cost of electricity generation from biomass, including capital and operational costs (\$/kWh)	0.046
Levelised cost of electricity generation from alternative fuel (diesel), including capital, operational and fuel costs (\$/kWh)	0.3
Inventory capacity (tonne)	600

5.4.2.4. Transportation Module

This study considers multi-modal transportation networks, integrating trucks for transporting materials from suppliers to bio-hubs and ships for deliveries from bio-hubs to remote communities. As depicted in Figure 5.3, the travel time begins as soon as the vehicles are dispatched. During the loading phase, destination details and related parameters are assigned to these agents. Upon reaching their destinations (i.e., bio-hubs or remote communities), the unloading process is initiated, and travel time is ended. At this stage, the inventory records for these facilities are adjusted: on-order inventory decreases, while on-hand inventory increases by the amount corresponding to a full truckload or shipload. Furthermore, the total operational time required for loading and unloading procedures is calculated based on the specific loading and unloading durations of these vehicles. In this research, a working schedule of 7 days with two shifts per day, operating from 7 am to 10 pm with a rental cost of 35 (\$/h), is assumed for trucks. Additional details about these operational requirements are provided in Table 5.4 (Mobini et al., 2014; NEAS, 2024).

Table 5.4. The inputs of transportation modules

Fleet	Weight capacity (tonne)	Fuel consumption rate	Average speed (km/h)	CO ₂ eq. emission (kg/lit)	Load/Unload time (min)
Truck	10	U (0.2,0.3) (lit/km)	U (50,100)	2.7	U (60,120)
Ship	17	3.7 (g/tonne km)	U (30,40)	3.06	U (120,180)

5.5. Results and Discussion

The entire network is simulated for one year (i.e., 8760 h), starting from 1st January until 31st December. Considering the scale and number of decision variables, the simheuristic process was set to run for 500 iterations, each with 100 independent replications, which satisfies the

conditions of the Central Limit Theorem (Ott and Longnecker, 2016) and ensures that the distribution of sample means approximates normality. This supports the reliability of the simulation results, confirms the convergence of outcomes, and consequently enhances the validity of findings (Saisridhar et al., 2024). Moreover, the standard error of mean (SEM) is calculated for two critical KPIs of electricity generation from biomass and total cost. The SEM provides a measure of the variability or precision of the sample mean estimates obtained from different simulation runs (Geroldinger et al., 2023). By examining the SEM, the extent to which these KPIs converge as the number of iterations and replications increases can be assessed. A lower SEM indicates that the sample means are more tightly clustered around the true mean, suggesting a higher degree of reliability in the simulation results. Figure 5.5 illustrates that as the number of replications increases, the SEM declines, indicating the simulation results for both electricity generation and total cost become more stable and converge toward their expected values. Notably, after 80 replications, the SEM for KPIs exhibit a consistent trend.

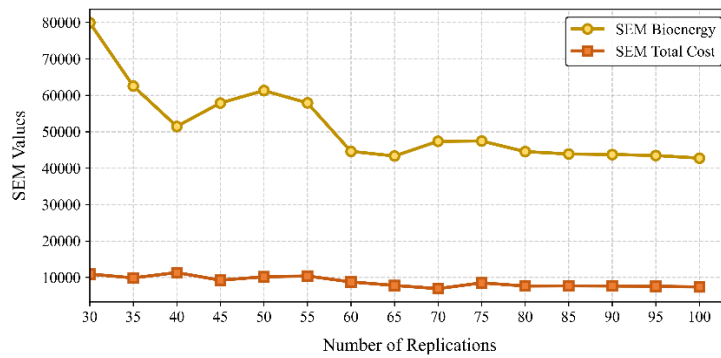


Figure 5.5. SEM evaluation of bioenergy production and total cost of the proposed BSC

Moreover, this study builds on the established simulation validation approaches in the literature for validating the results (Saisridhar et al., 2024). These approaches include benchmark scenario testing, sensitivity and degenerate tests by varying key parameters or selectively removing model components, and additional experiments using alternative optimization methods to ensure result robustness. To this end, a comprehensive sensitivity analyses is conducted on parameters such as feedstock quality, equipment breakdown, inventory monitoring periodicity, and transportation capacity to ensure the model produces robust and realistic outputs under varying conditions.

5.5.1. Analysis of the Results

Upon completing the required iterations and replications, a set of solutions for s and S is achieved (see Table 5.5). The replenishment strategies employed by hubs are guided by the

quantity of the finished products rather than raw feedstock to maintain the continuous availability of high-quality wood pellets for community use. Notably, the inventory monitoring is structured on a daily basis, which reflects the periodicity of one day.

Table 5.5. The obtained solution for (s, S)

Node	Inventory policy (s, S)		Node	Inventory policy (s, S)	
	s (tonne)	S (tonne)		s (tonne)	S (tonne)
Eastmain	410	900	Inukjuak	370	375
Bathurst	340	640	Puvirnituq	420	595
Kangiqsujaq	270	320	Kangiqsualujjuaq	245	310
Salluit	190	365	Akulivik	280	345
Ivujivik	75	135	Kuujuarapik	485	505
Kuujjuaq	575	600			

Once the (s, S) parameters are established, the developed simulation model is implemented to calculate KPIs. One of the primary outputs of this model is electricity generation from either biomass or diesel. Figure 5.6 reveals that bioenergy consistently dominates the energy mix in all communities. Specifically, bioenergy supplies a total of 42.82 GW, while unmet demand is met by diesel, which contributes 35.98 GW. This results in bioenergy comprising nearly 55% of the total electricity mix, underscoring its potential to be the main energy source in long-term.

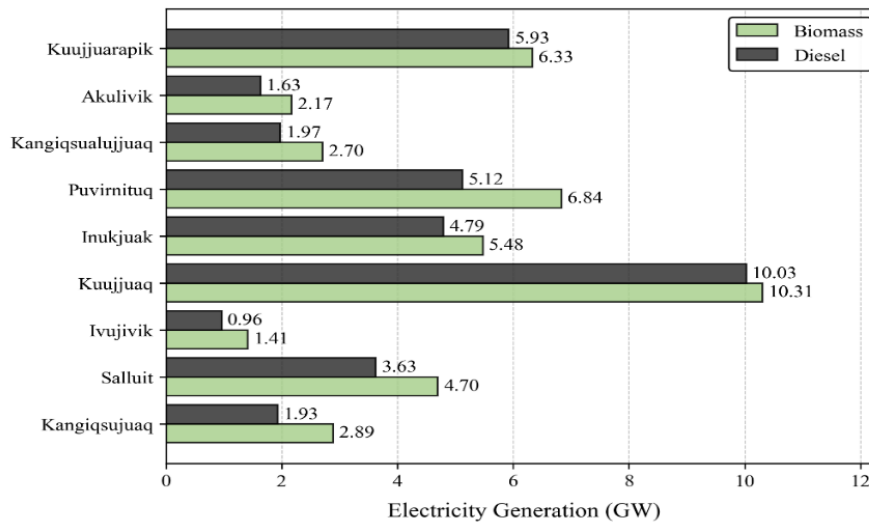


Figure 5.6. Electricity generation mix in remote communities of Quebec

To promote bioenergy consumption in these communities, a penalty is considered in the electricity generation cost function to discourage diesel use. This incentivizes the model to favor biomass, which is aligned with the sustainability objectives of government programs (CER, 2024). In our simulation-optimization framework, the penalty does not distort near-optimal solutions, while narrowing the search space by discouraging costly diesel-heavy

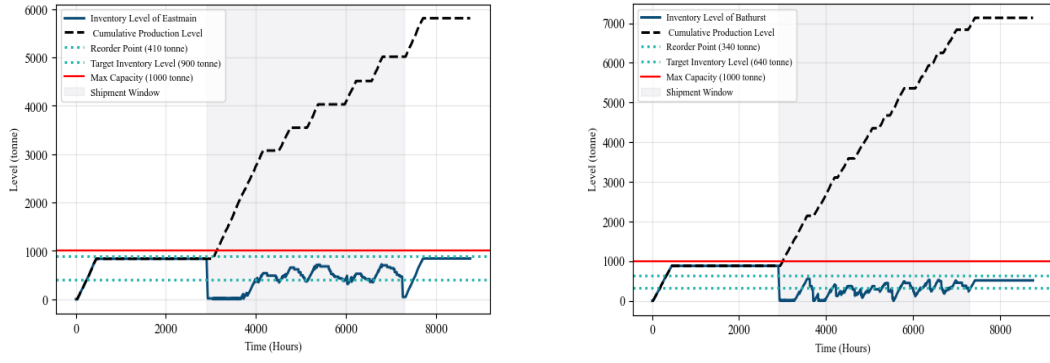
options and accelerating convergence. Consequently, the model not only remains cost-conscious but also promotes maximum biomass utilization, aligning with environmental and policy objectives (Yavari and Bohreggi, 2025).

Another important KPI in this study is CO₂ emission. In addition to truck and ship transportation, the conversion of biomass and diesel into electricity further contributes to the overall carbon emission footprint. According to the National Renewable Energy Laboratory (NREL, 2021), biomass burning for electricity generation results in 0.052 kg CO₂. eq/kWh, while diesel contributes a much higher rate of 0.840 kg CO₂. eq/kWh. This data is then used to calculate total CO₂ emissions. Results show that the proposed dual sourcing scenario significantly reduces overall emissions compared to a scenario where only diesel is used (see Table 5.6). These findings highlight the potential of bioenergy to meet energy demands while contributing to sustainability goals through the reduction of greenhouse gas emissions.

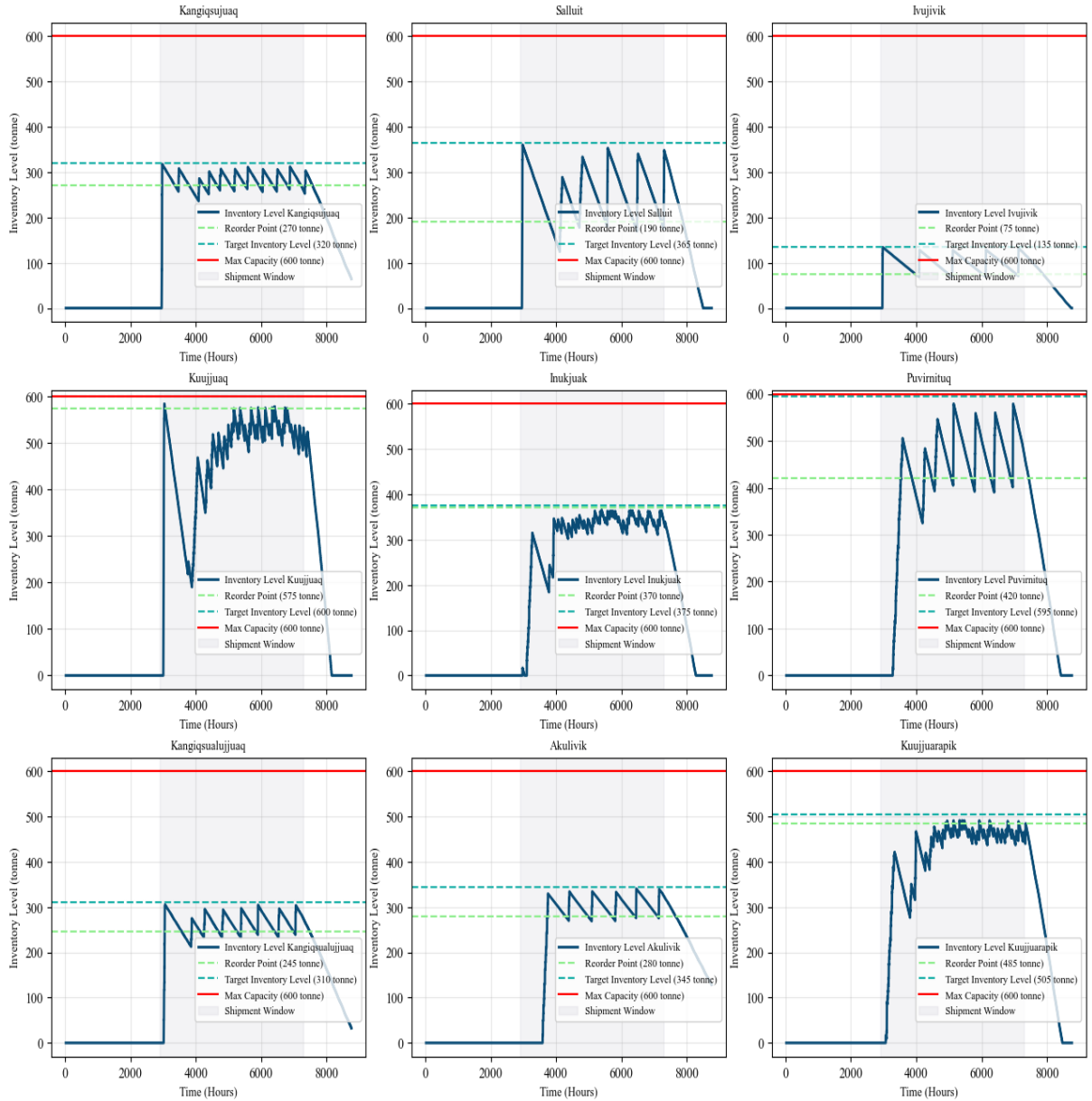
Table 5.6. CO₂ emission from transportation and electricity generation

Activity	Kg CO₂ eq.
Truck transportation	805,610
Ship transportation	444,521
Biomass burning	2,226,868
Diesel burning	30,228,763
Total emission (dual sourcing scenario)	33,705,762
Total emission (diesel-only scenario)	66,201,240

To provide a deeper understanding of the system's operational dynamics, Figure 5.7 illustrates the temporal changes in inventory levels and production rates at bio-hubs, alongside the dynamic inventory levels across various remote communities over the simulation runtime. It shows how these variables adapt to shifting demand and supply conditions throughout the simulation. In the proposed model, the production line pauses the conversion of sawdust into wood pellets whenever the combined amount of on-hand wood pellet inventory and in-process materials in the machinery exceed the bio-hubs' inventory capacity, which is assumed 1,000 tonnes. This constraint prevents overproduction and ensures that storage limitations are not exceeded, thereby minimizing the risk of material wastage. Following this, it can be seen that the inventory remains constant within the bio-hubs until the transportation window opens in May (at 2900 hours). After this point, inventory levels decrease sharply as hubs receive a large volume of demand. The production line also does not demonstrate a significant increase in output after this period, as demand remains high, and produced material must be allocated to meet the needs of the communities.



(a)



(b)

Figure 5.7. Inventory level dynamics under (s, S) policy: a) bio-hubs and b) remote communities

As depicted in this figure, there is a noticeable delay in the receipt of wood pellets in communities until the transportation time window opens. During these periods, communities are unable to procure the necessary biomass resources, which leads to an increased diesel share. The quantity of orders placed each time is not static and fluctuates in response to the varying demand patterns observed throughout the year. Implementing the (s, S) inventory policy enables communities to adapt their ordering strategies and optimize stock levels to meet real-time demands, while minimizing excess inventory. In some communities, inventory levels occasionally fluctuate around the reorder point during shipment windows due to the dynamic interaction between consumption rates and transit times. In higher-demand communities such as Inukjuak and Kuujjuarapik, inventories remain below the reorder point because their consumption levels exceed the replenishment capacity of standard shipment sizes and frequencies. Nevertheless, despite inventories remaining below the threshold, these communities achieve a bioenergy share of approximately 55%, which surpasses their reliance on diesel. The observed inventory patterns are further influenced by storage capacity limitations and the specific bio-hub assigned to each community, since shipment timing and available transport capacity vary geographically. Collectively, these results demonstrate the model's ability to capture the operational characteristics of the proposed BSC network, including heterogeneous demand, proportional allocation, transit delays, and geographical dispersion.

Figure 5.8 provides a detailed breakdown of cost components, which highlights potential areas for cost minimization and illustrates the impact of different factors on the total cost. As can be seen, the inventory and transportation costs are the largest contributors to bio-hub costs, accounting for 50% and 37.08% of the module costs, respectively. These figures underscore the importance of efficient inventory management, as inventory costs can quickly rise with overproduction, and transportation expenses can increase due to inefficient ordering practices. For remote communities, diesel-based electricity generation is the largest contributor, accounting for 55% of the communities' total costs and 51% of the overall BSC cost. In contrast, bioenergy generation contributes only 10% to the total cost while supplying nearly 55% of the electricity. Moreover, results indicate a decrease in the unit cost of electricity (as a measure of economies of scale) from 0.30 \$/kWh in the diesel-only scenario, with a total annual cost of \$23.8 million. Under the dual-sourcing configuration, this value declines to 0.26 \$/kWh, corresponding to a total cost of \$20.82 million. The unit cost in each scenario was obtained by dividing the total annualized electricity generation cost by the total electricity demand over a one-year period. Moreover, results indicate a decrease in the unit cost of electricity (as a

measure of the economies of scale), from 0.30 \$/kWh in the diesel-only scenario to 0.26 \$/kWh under the biomass-diesel configuration. This unit cost is derived by dividing the total cost of each scenario by the total electricity demand over the duration of one year. This reduction demonstrates the importance of bioenergy in promoting energy sustainability in these communities, as it not only provides a cost-effective alternative to fossil fuels but also contributes to reducing greenhouse gas emissions.

To assess the sensitivity of the proposed BSC network to inventory-related expenses, variations in hub and community-level inventory costs are analyzed to quantify their impact on KPIs. Results show that increasing hub-level inventory cost from \$2 to \$10 reduces biomass utilization by 6.56% while increasing diesel consumption by 5.42%. Total system cost rises modestly, and total CO₂ emissions increase by 4.60% (see Figure 5.8c). As hub inventory cost comprises approximately 4% of total cost, moderate adjustments lead to slight shifts in resource allocation and KPIs. However, extreme increases result in noticeable effects. At the community level, raising inventory cost from \$4 to \$8 decreases biomass share by 6.37%, increases diesel reliance by 5.26%, and elevates total cost and CO₂ emissions by 1.85% and 4.47%, respectively. Inventory cost of communities accounts for roughly 11.4% of total system cost, making KPIs at this level more sensitive to cost changes. These findings emphasize the importance of optimizing inventory policies at both hubs and communities to balance biomass utilization, diesel dependency, system cost, and environmental performance. While these findings are based on the regional context, the methodological framework is adaptable to other regions facing similar challenges. In such settings, biomass can serve as a reliable complement or substitute for conventional fuels to strengthen energy security, reduce reliance on costly external deliveries, and support sustainable energy transitions in geographically constrained communities.

5.5.2. Sensitivity and Uncertainty Risk Factor Analysis

In the SC resilience literature, various studies have proposed approaches to quantify network resilience, typically categorized as operational, structural, or financial metrics (Taghizadeh et al., 2021; Habibi et al., 2023b; Jabbarzadeh and Shamsi, 2025). Acknowledging that resilience is multi-dimensional and requires strategies that balance efficiency with sustainability and robustness, this study adopts operational metrics such as bioenergy production and the unmet bioenergy demand ratio, along with a financial KPI of unit cost as resilience measurements. CO₂ emissions are also included to reflect the trade-off between resilience and sustainability. The amount of biomass combustion, and therefore emissions, depends directly on the system's

resilience in terms of the feedstock amount it can supply. In contrast, diesel combustion produces approximately 16 times more CO₂ than biomass for the same energy output, highlighting the environmental cost of relying on diesel-dependent operations. These KPIs collectively provide a comprehensive measure of the system's performance and sensitivity under different operational scenarios. This section provides a comprehensive analysis of how risk factors and disruptions can affect the results.

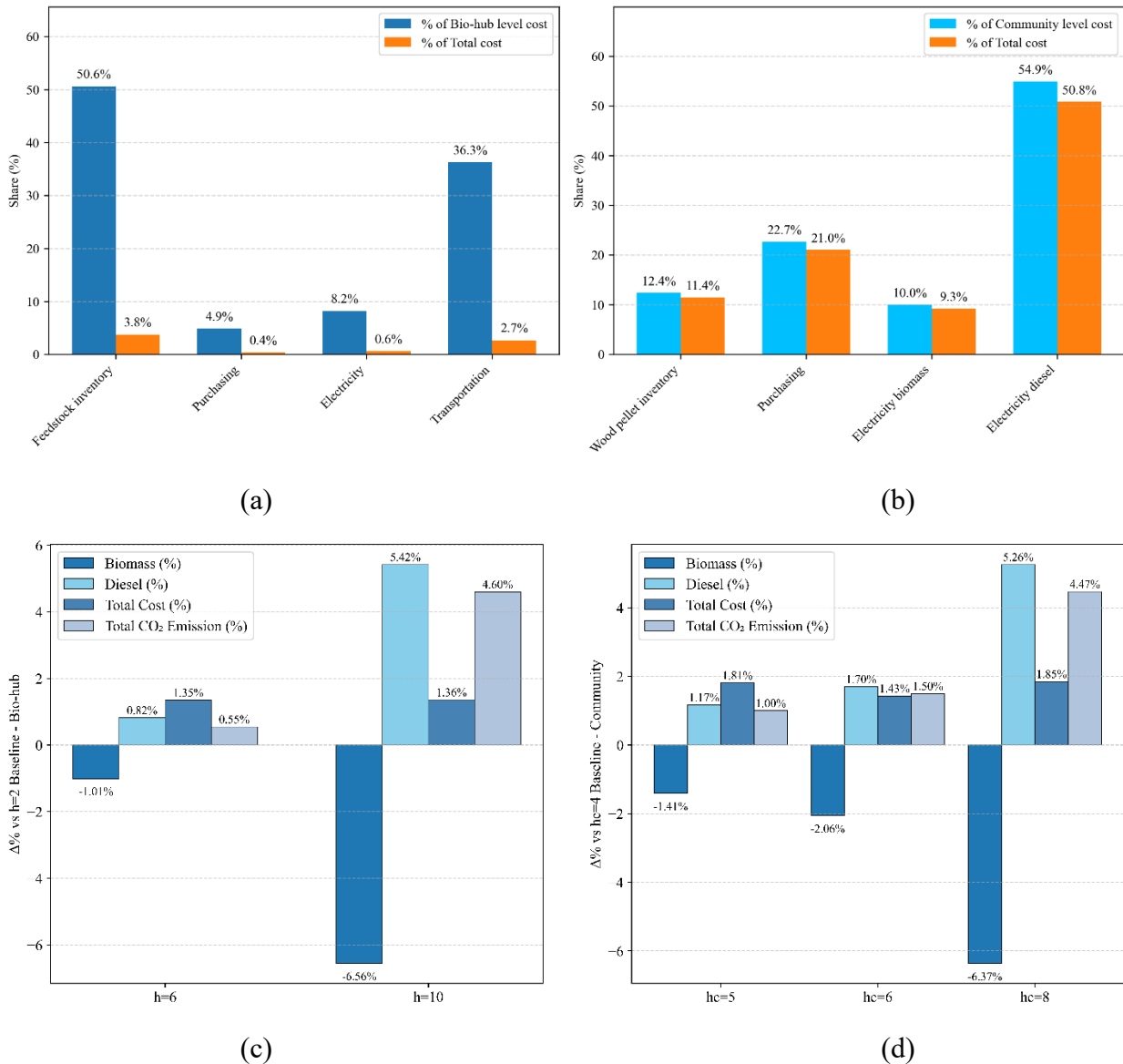


Figure 5.8. Cost component shares in the proposed BSC network: a) bio-hub module, b) community module, c) inventory cost analysis of bio-hub module, and d) inventory cost analysis of community module

5.5.2.1. Equipment Breakdown

A disruption analysis of biomass processing machines within bio-hubs reveals how both the intensity and simultaneity of equipment failures propagate through the network and affect energy output, cost, and emissions. As shown in Figure 5.9, in the first scenario, where individual machines experience disruptions with short repair times (Exp 2-1 h), the impacts are moderate, which highlights the system's relative resilience to isolated, short-term interruptions. The drum dryer, being high-capacity and energy-intensive, shows the largest reductions in electricity from biomass and increases in the unmet demand, whereas hammer mills, pellet mills, and coolers exhibit smaller but non-negligible effects due to their role in downstream processing. Second scenario extends repair times (Exp 4-2 h) to model high-intensity failures. In this scenario, the drum dryer disruption leads to dramatic drops in electricity production and substantial increases in unmet bioenergy demand, while other machines also experience heightened impacts. This behavior reflects non-linear propagation of downtime through the network. Last scenario simulates simultaneous moderate-intensity disruptions of all machines, which represents correlated failures or cascading events. Results show that electricity from biomass declines by 28.74% and unmet demand rises by 34.2%, with associated increases in costs and CO₂ emissions. These findings demonstrate that system vulnerability is highly sensitive to both the failure intensity of individual machines and their simultaneous disruption.

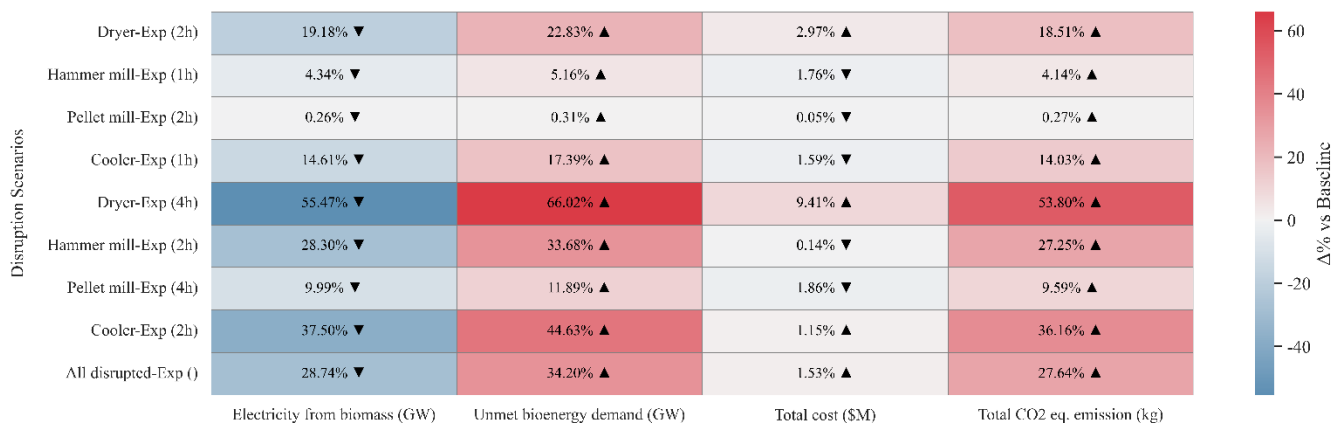


Figure 5.9. Impact of machine-specific disruptions on KPIs

5.5.2.2. Feedstock Quality

In biomass-based energy systems, MC and HV are two important quality attributes that affect operational outputs of the network. The sensitivity analysis shown in Figure 5.10 demonstrates that HV is negatively correlated with feedstock amount sent by suppliers, truck deployment,

and total system cost. An increase in HV enhances the energy density of biomass and reduces the volume of material required, lowers transportation intensity, and decreases overall cost. Conversely, MC shows a positive correlation with these KPIs. Higher MC decreases the effective energy content per unit of biomass, necessitating additional feedstock procurement and truck movements. Importantly, the analysis indicates that MC variations demonstrate a stronger marginal effect than HV, with incremental increases in MC leading to higher growth in both cost and logistics requirements. These results emphasize the critical role of feedstock quality control in BSCs. In particular, MC emerges as a dominant driver of system inefficiency that intensifies direct economic costs and indirect environmental impacts through increased transport activity and energy use.



Figure 5.10. Impact of Feedstock quality on KPIs

5.5.2.3. Inventory Monitoring Frequency

In SC operations, the synchronization of inventory management and decision-making frameworks directly affects an organization's ability to adapt to changing market demands while ensuring operational efficiency (Stranieri et al., 2024). Inventory control parameters, such as monitoring frequency, are closely associated with the timing and precision of stock assessments. This parameter influences operational factors, including reorder points, order quantities, and resource allocation, and serves as an important determinant in achieving a balance between operational efficiency and cost-effectiveness. To this end, a comprehensive sensitivity analysis was conducted to evaluate the impact of inventory monitoring periodicity on KPIs, comparing daily, weekly, and bi-weekly assessments. Heatmaps are provided to visually illustrate how variations in monitoring frequency affect system performance (see Figure 5.11). The analysis relating to daily operations shows a clear trade-off between operational efficiency, energy supply reliability, and environmental performance. Moving from

daily to weekly monitoring increases total cost by 1.31%, reduces bioenergy availability by 5.87%, and raises diesel consumption by 6.60%, which indicates a slight decline in system responsiveness. Less frequent monitoring lowers truck and ship utilization and consequently reduces transportation-related emissions. However, total CO₂ emissions rise by 5.39% because of higher diesel dependence. Extending the interval to bi-weekly monitoring further decreases bioenergy supply by 9.09% and increases diesel reliance by 10.82%, which leads to greater unmet bioenergy demand and delayed deliveries. Fleet requirements decline more sharply, and transportation-specific emissions fall, yet total CO₂ emissions increase by 8.79%, demonstrating that logistics efficiency gains cannot offset the environmental impact of additional diesel use. These results confirm the fundamental trade-off between monitoring frequency, supply reliability, and decarbonization objectives, with daily monitoring providing the most balanced outcome in terms of cost, energy security, and environmental performance.

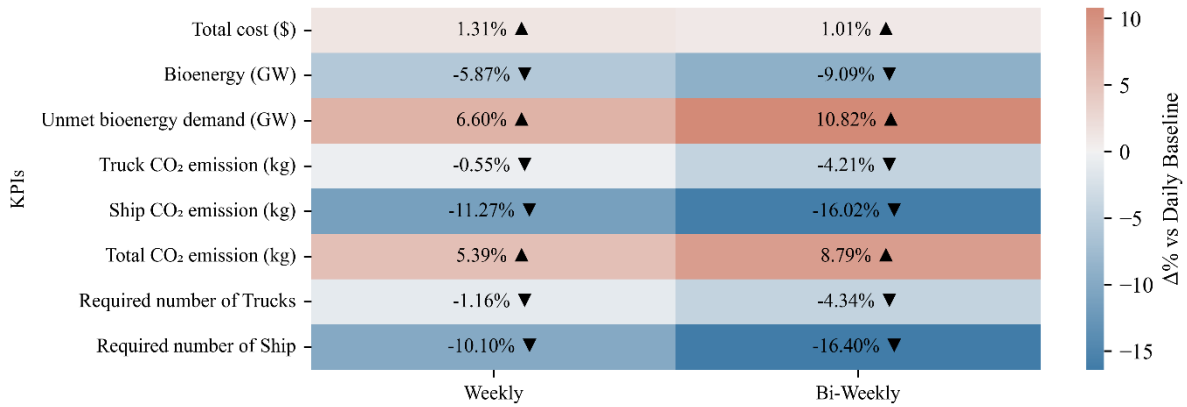


Figure 5.11. Effect of inventory monitoring frequency on KPIs

5.5.2.4. Fleet Capacity

Effective logistics planning is a cornerstone of SC optimization, where the capacity of key resources, such as transportation fleets can significantly influence the performance of whole network (Yalcin and Daim, 2022). In this context, parameters that are often treated as constants in modeling procedures are fundamental in determining the system's behavior. The sensitivity analysis on truck capacity reveals important insights into the interplay between fleet capacity, total cost, bioenergy generation, and CO₂ emission. As shown in Figure 5.12, the sensitivity analysis on truck capacity relative to the 10-tonne baseline reveals nonlinear trade-offs across cost, energy mix, and environmental KPIs. Reducing capacity to 5 tonnes markedly increases operational requirements, reflected in a sharp rise in fleet size and corresponding growth in truck-related CO₂ emissions, despite marginal reductions in ship usage. This is expected, as

smaller vehicles necessitate a greater number of trips to satisfy the same demand, thus increasing logistics intensity and associated emissions. Conversely, scaling capacity upward to 20 and 30 tonnes reduces the number of trucks significantly, which lowers truck-kilometer exposure and associated emissions by 39.79% and 57.40% respectively. However, these gains are offset by increased unmet bioenergy demand and higher diesel reliance, suggesting that oversized trucks lead to less frequent deliveries, insufficient replenishment, and consequently a reduction in service reliability. From a cost perspective, the 20-tonne case shows marginal improvement, while the 30-tonne case yields a 3% cost increase, primarily driven by the compounded effects of demand shortfalls and greater diesel substitution. The total CO₂ emissions follow a similar pattern, where larger trucks reduce transport-specific emissions, but the indirect emissions from higher diesel use dominate, which lead to a net increase compared to the baseline (i.e., 13%). These results demonstrate that undersized fleets increase direct emissions and operational costs, while oversized fleets compromise supply reliability and elevate system-level emissions through imbalances in the energy mix. The baseline 10-tonne configuration thus emerges as an operationally balanced point, minimizing both logistical inefficiency and reliability risk.

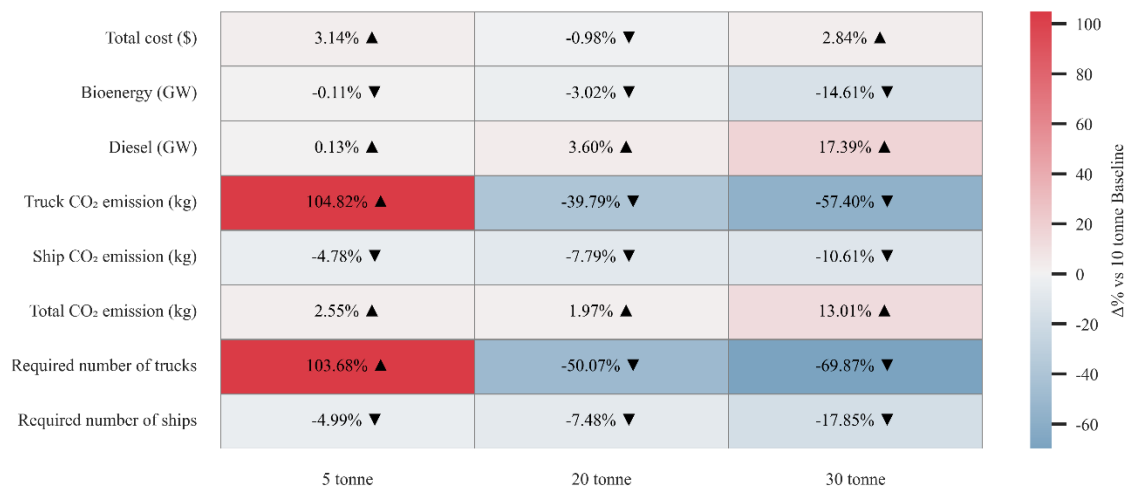


Figure 5.12. Effect of fleet capacity on KPIs

5.5.2.5. Optimization Algorithm

In this sub-section, an alternative algorithm is employed to validate the results obtained from the GA. The OptQuest Engine is a powerful optimization tool integrated into AnyLogic as an optional add-in to guide its search mechanism toward better solutions (Vieira et al., 2023). It applies a combination of metaheuristics, such as TS and SS to optimize simulation outcomes by varying controllable parameters. By combining these algorithms into a composite search

method, OptQuest identifies the solutions that maximize or minimize a model's objective function (Seçkiner and Koç, 2022). The analysis of the algorithm's performance reveals a consistent tendency to maintain inventory levels near maximum capacity across various scenarios. This behavior which is evident in Figure 5.13, suggests that the facilities prioritize stock preservation to mitigate the risk of shortages. However, the algorithm's focus on exploitation rather than exploration, may lead to convergence without exploring diverse regions of the solution space. This indicates a potential limitation in efficiently exploring the solution space, which may constrain optimal resource allocation (Hussain and Muhammad, 2022). Although the OptQuest algorithm achieves a marginal increase in bioenergy generation compared to the GA's output, it is essential to evaluate associated cost implications. OptQuest results in a unit cost of 0.28 \$/kWh, whereas the GA produces a lower unit cost of 0.26 \$/kWh. Furthermore, the findings indicate that as the inventory checking duration increased, a noticeable reduction in biomass allocation occurs which leads to a corresponding decline in bioenergy production. This trend aligns with the findings from the GA.

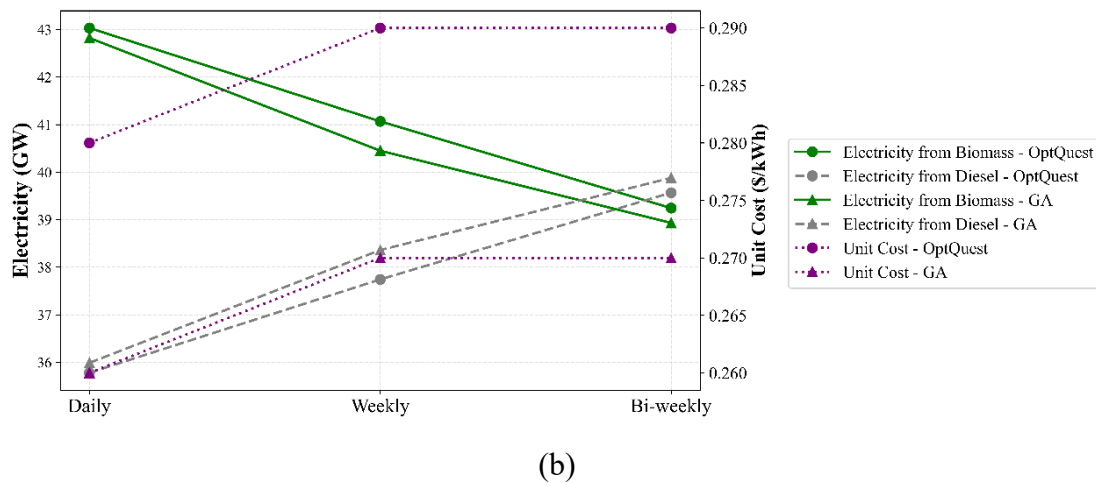
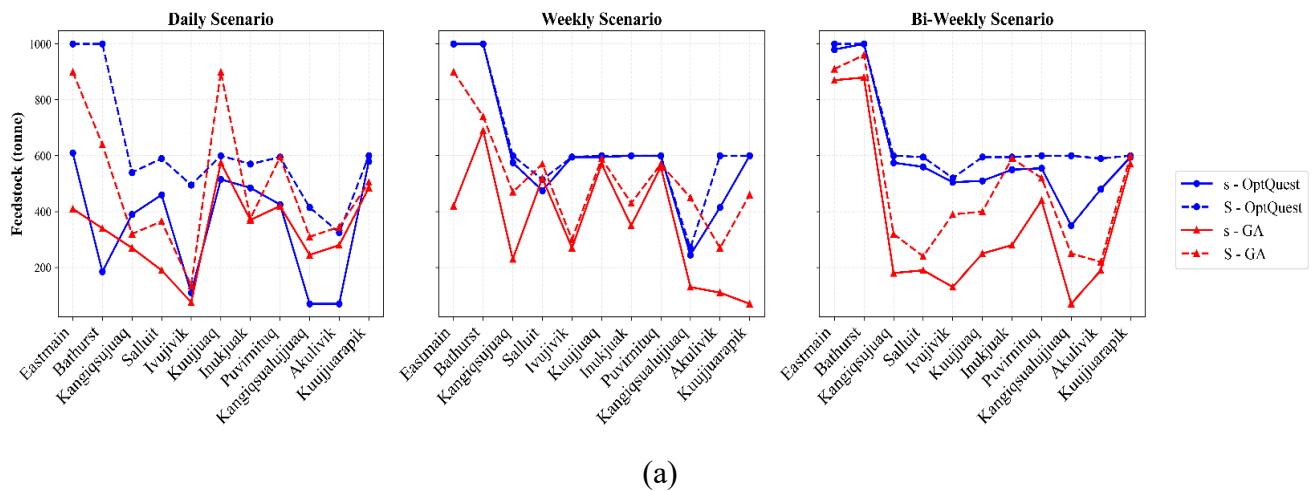


Figure 5.13. Comparative analysis of GA and OptQuest: a) inventory levels (s , S), b) operational KPIs

5.6. Discussion of Implications

5.6.1. Theoretical Implications

A fundamental theoretical advancement of this research lies in conceptualizing inventory policy as an integrated, multi-echelon coordination problem under an uncertain environment specific to BSCs. Traditional inventory theories predominantly focus on single-echelon or decentralized policies assuming normal distribution for demand and lead time, which inadequately represent the interdependent and time-sensitive nature of inventory decisions in renewable energy networks, where supply variability, perishability, and seasonal logistics critically interact. This study introduces a novel framework that reconceptualizes inventory management as a dynamic, interdependent process, where replenishment decisions at upstream bio-hubs and downstream conversion facilities are jointly optimized to mitigate cascading uncertainties and balance cost-environment trade-offs. By embedding this policy within a stochastic environment, the framework reveals emergent properties of inventory behavior, such as adaptive stock adjustments that challenge classical assumptions of inventory control and open new theoretical pathways for understanding multi-tier inventory dynamics in volatile, capacity-limited contexts. Moreover, the proposed architecture formalizes the structural, behavioral, and decision-making components that constitute the conceptual basis for digital twin applications in biomass-integrated energy networks. By synthesizing ABS and DES within an optimization-driven decision framework, it articulates a replicable methodological template for representing complex multi-echelon SC networks under uncertainty. This work advances the theoretical discourse on digital twins by demonstrating how high-fidelity virtual models can be systematically configured to capture stochastic variability, operational constraints, and inter-tier feedback mechanisms. The developed framework also provides a robust theoretical foundation that can be extended to incorporate continuous data assimilation, thereby enabling dynamic synchronization between physical and virtual systems and fostering prescriptive, adaptive decision-making in renewable energy SCs.

5.6.2. Managerial Implications

This research offers actionable insights for policymakers working toward a more sustainable and secure energy transition to renewable ones. It closely aligns with the broader agenda of the United Nations 17 Sustainable Development Goals (SDGs), specifically SDG 7 and SDG 13. For SDG 7, which emphasizes access to affordable and clean energy, the results provide strategic guidance for managers and policymakers on integrating biomass into local energy

systems, particularly in regions that currently rely on diesel. By highlighting the cost-effectiveness, local availability, and storability of biomass, the study supports decisions that improve energy accessibility and reliability while reducing dependency on fossil fuels. For SDG 13, which focuses on urgent climate action and reducing greenhouse gas emissions, the findings demonstrate how substituting diesel with biomass can substantially lower CO₂ emissions, helping organizations and communities align with net-zero and carbon reduction targets. These insights are also directly relevant to programs such as Canada's clean energy for rural and remote communities (CER, 2024). This program has been developed to accelerate this transition by funding renewable energy initiatives and reducing dependence on fossil fuels. The current research can contribute to such decarbonization programs by highlighting the strategic importance of low-carbon BSCs as a scalable pathway. Beyond emissions reductions, investing in clean energy for indigenous and remote communities enhances energy security, fosters self-determination, and contributes to broader reconciliation efforts. Furthermore, by presenting a viable model for transitioning to bioenergy, the framework strengthens the investment case for both public and private stakeholders, thereby accelerating the shift toward resilient and low-carbon energy systems.

5.6.3. Practical Implications

Building on these insights, the proposed study provides a DSF that allows practitioners to evaluate trade-offs among cost, reliability, and environmental impact in bioenergy supply systems. It offers a scalable solution for addressing energy volatility across diverse geographic, economic, and policy landscapes. Although developed for northern Canada, the proposed DSF can be adjusted and replicated in other regions facing energy insecurity and planning for scalable, low-carbon energy solutions. Its modular architecture enables the integration of heterogeneous data sources, logistical constraints, and policy incentives, ensuring adaptability to different renewable technologies and market conditions. To ensure that this adaptability translates into tangible resilience outcomes, the framework integrates risk mitigation strategies such as redundancy through dual-sourcing and localized inventory buffering. Such strategies define how energy systems can withstand and recover from disruptions, while also advancing sustainability and security goals (Rajabzadeh and Wiens, 2024). Diesel functions as a contingency energy source to maintain operational continuity during transport delays or biomass shortages, while community-level wood pellet storage provides another layer of redundancy, buffering against seasonal shipping constraints. This dual-source strategy reflects the logic of multi-sourcing, where different resources reinforce one another to enhance system robustness (Yavari and Bohreggi, 2025). These findings guide practitioners on how to

dimension and schedule backup inventory levels to sustain service reliability in harsh and logistically constrained environments. Importantly, these measures are specifically tailored to the unique geographical and infrastructural constraints of remote communities that depend on seasonal waterways. By simulating the impact of risk factors in real-world scenarios, practitioners can make evidence-based decisions that simultaneously reduce greenhouse gas emissions, enhance energy reliability, and balance costs.

The findings of this study offer critical implications for the operations of biomass-based energy systems. The model demonstrated that bioenergy could supply 55% of total electricity demand, which confirms its potential to serve as a reliable primary source for remote regions. This result implies that hybrid energy configurations can reduce reliance on diesel and strengthen long-term energy autonomy and security. Moreover, achieving an approximately 14% reduction in unit electricity cost provides quantitative evidence of the economic advantages of the proposed configuration. This demonstrates that a dual-sourcing mechanism, supported by coordinated replenishment and multimodal transportation planning, can enhance cost efficiency while maintaining service reliability. The 49% reduction in CO₂ emissions relative to diesel-only configurations demonstrates that integrating biomass within existing energy systems can deliver significant environmental benefits aligned with national decarbonization targets. Sensitivity analyses also revealed that marginal variations in fleet capacity and inventory monitoring periodicity lead to notable shifts in emissions and total cost, which indicates that system performance is highly dependent on operational calibration. The feedstock quality analysis identified MC as a dominant driver of inefficiency, as higher MC increases transport intensity, total cost, and carbon emissions. This highlights the need for upstream quality control through improved drying infrastructure or supplier standards to stabilize energy density and enhance system productivity. Finally, the model showed that rising inventory holding costs shift energy reliance toward diesel, raising both total system cost and emissions. Decision-makers can mitigate these adverse effects by incentivizing pellet storage through targeted subsidies or low-interest financing mechanisms that encourage inventory buffering at both bio-hubs and communities. Collectively, these findings imply that planners should adopt adaptive BSC planning frameworks that continuously tune operational parameters to maintain economic efficiency, reliability, and environmental sustainability.

5.7. Conclusions

Considering the critical role of inventory management in mitigating SC disruptions, especially in energy SCs, this study has proposed a new DSF to establish a systematic replenishment strategy under uncertain and dynamic conditions. To this end, the proposed DSF integrated the

strengths of ABS, DES, and optimization via simulation technique to model an intertwined multi-echelon and multi-tier BSC network and navigate the complexity of the problem under study. This framework accounted for a wide range of uncertainties, which were systematically fed into the model through probability distributions. Given its computationally expensive function and large solution space, GA and OptQuest were integrated with the simulation model to find near-optimal solutions for inventory-related decision variables under defined constraints, while optimizing the objective function. The findings implied that integrating biomass into the energy mix decreases the electricity unit cost while presenting a viable and sustainable pathway for becoming a dominant energy source. In the case study of remote communities, the proposed dual sourcing scenario demonstrated a 14% reduction in the unit cost of electricity and a 49% reduction in CO₂ emission compared to a diesel-only scenario. Moreover, the choice of inventory monitoring intervals significantly influenced bioenergy share, cost, and CO₂ emission within the network. Considering the operational and transportation constraints, daily monitoring yielded better results in terms of KPIs compared to weekly and bi-weekly monitoring. While larger trucks theoretically offer greater efficiency by reducing the number of trips, the combined effects of full-load requirements and transportation time window limitations reduced the actual frequency of biomass deliveries. This led to increased reliance on diesel, raising both operational costs and environmental impacts.

The current work could be further enhanced by incorporating machine learning techniques to forecast seasonal demand variations, with outputs integrated into the simulation model to better capture real-world fluctuations and improve planning accuracy. Diesel transportation could also be modeled with greater detail to more accurately represent associated costs and CO₂ emissions. Moreover, extending the model to include multiple biomass feedstocks and alternative conversion processes, such as torrefaction, would enhance operational flexibility and enable a more comprehensive assessment of technological pathways under varying conditions.

Chapter 6: A Bi-Level Optimization Approach for Resilient Logistics Planning in Biomass Supply Chains

6.1. Introduction

In today's interconnected and turbulence-prone global economy, logistics planning has become a cornerstone of supply chain management (SCM), shaping operational efficiency, resilience, and sustainability (Ebrahimi et al., 2025). Far from being isolated decisions, logistics activities such as inventory allocation, multimodal transportation scheduling, fleet deployment, and facility utilization are highly interdependent. A single misaligned decision at one node can propagate across the entire network, triggering ripple effects that distort upstream and downstream flows. These disruptions can amplify costs, create bottlenecks, reduce asset utilization, and ultimately compromise service continuity and overall supply chain (SC) resilience (Aldrighetti et al., 2021; Habibi et al., 2023b). This systemic interdependency is further intensified under uncertainty, arising from fluctuating demand, supplier disruptions, seasonal capacity constraints, or geopolitical shocks, which require SCs to prepare proactively rather than reactively for potential disruptions (Olivares-Aguila and ElMaraghy, 2021). In this context, coordination mechanisms are essential for ensuring that logistics decisions are systematically aligned across multiple entities, echelons, and planning horizons (Abideen et al., 2023). By facilitating real-time information exchange, integrated resource allocation, and the harmonization of tactical and operational decisions, these mechanisms significantly enhance the network's capacity to absorb disruptions and sustain service performance.

Within this broader landscape, biomass supply chains (BSCs) represent a particularly challenging and strategically significant application domain, where the role of coordinated logistics planning becomes even more critical (Gital and Bilgen, 2024a). The accelerating global warming crisis and the gradual depletion of fossil fuel reserves highlight the urgency of transitioning toward renewable alternatives such as biomass-based energy. While wind and solar require substantial infrastructure investment, bioenergy offers a comparatively faster, cost-effective, and flexible pathway, with significant environmental and economic benefits (Mafakheri et al., 2021). Biomass not only reduces CO₂ emissions but also provides versatility through the production of biofuels, electricity, and value-added chemicals, which makes it more adaptable and widely accessible than other renewable technologies. However, the realization of bioenergy's potential is constrained not only by technological and feedstock availability challenges but also by the efficiency and resilience of its logistics operations

(Zhang and Bin, 2025). For instance, wood pellets logistics costs can range from 34 % to 77 % of the total SC costs (WBA, 2018). In some cases, logistics costs account for up to 90 % of the total cost of raw materials (Malladi and Sowlati, 2018), highlighting the critical importance of carefully planned and efficiently executed SCM to reduce expenses and improve overall system performance. Efficient management can significantly reduce operating costs and increase profits while also having a positive influence on the sustainable SC (Verma, 2024). Optimizing logistics processes allows for faster and more reliable delivery of items, which in turn improves customer satisfaction and loyalty. In addition, efficient inventory and transportation management minimizes losses and waste, and increases a company's flexibility and ability to respond quickly to market changes. As a result, well-organized logistics contribute to better performance and increased competitiveness.

Despite its importance, integration of logistics and BSC operations remains limited by several persistent challenges, such as variability in biomass quality (Razm et al., 2025), disruption in supply availability (Valipour et al., 2024), the complexity of synchronizing BSCs with heterogeneous logistics profiles (Abideen et al., 2023), and limited scalability of shared systems (Ebrahimi et al., 2025). Addressing these challenges requires advancing preprocessing compatibility, embedding adaptive and disruption-aware transportation planning, and fostering stronger coordination across stakeholders to build resilient, efficient, and scalable biomass supply networks (Habibi et al., 2023a). Motivated by the above observations, the current research seeks to address the following research questions:

RQ1: How can integrated logistics planning frameworks be designed to jointly optimize transportation and inventory decisions in BSCs?

RQ2: How can operational and disruption risks be effectively incorporated into integrated planning, while accounting for ripple effects?

RQ3: How can adaptive coordination mechanisms enhance the robustness and sustainability of biomass logistics under uncertainty?

This study develops a bi-level derivative-free optimization (DFO) framework that integrates SC and logistics decisions under uncertainty within a multi-echelon BSC network in order to respond to the research questions. The decision environment is inherently nonlinear and highly interdependent, where deriving closed-form objective functions is computationally intractable. To address this challenge, the framework adopts a simulation-optimization approach, leveraging agent-based simulation (ABS) to capture stochastic dynamics, cascading effects, and tier-level interdependencies, while derivative-free metaheuristics explore the

solution space to identify effective replenishment and transportation planning strategies under uncertainty. The proposed network architecture comprises suppliers, bio-hubs, and power plants. At its core, bio-hubs serve as multifunctional intermediary nodes equipped with pelletization technology that enhances feedstock quality by reducing moisture content and synchronizes replenishment flows while enabling scalable storage for downstream energy conversion. The optimization process is structured into two sequential layers. In the first stage, fleet capacity constraints are temporarily relaxed to derive replenishment policies across hubs and demand nodes, accounting for uncertain supply availability and operational risks. In the second stage, transportation planning is optimized by incorporating heterogeneous fleets, multimodal transport options, and seasonal accessibility restrictions to align logistics execution with replenishment outcomes. Finally, based on the integrated replenishment and transportation solutions, the framework determines equipment capacities at bio-hubs and storage requirements at demand nodes to ensure resilience and efficient resource utilization. To demonstrate its applicability and relevance, the framework is validated through a case study of remote off-grid communities in northern Quebec, where extreme operational conditions highlight the necessity of resilient and well-coordinated BSCs.

The remainder of this study is organized as follows. Sections 6.2 and 6.3 describe the problem under study and introduce the proposed DFO framework, respectively. Section 6.4 presents an in-depth discussion of the results, including a sensitivity analysis of parameters that affect the outputs. Finally, Section 6.5 concludes the study with final remarks and recommendations for future research.

6.2. Problem Statement

The large-scale deployment of biomass as a renewable energy source is constrained not only by feedstock availability but also by the efficiency and resilience of its SCs. BSCs operate under volatile conditions, where variability in feedstock quality, seasonal supply disruptions, and limited transportation accessibility expose the network to cascading risks. These risks amplify logistics costs, reduce asset utilization, and jeopardize service continuity in energy delivery, particularly in remote and resource-constrained regions. While integrated planning frameworks hold promise for enhancing resilience, existing approaches often rely on simplifying assumptions, neglecting the ripple effects of disruptions and the nonlinear interdependencies between replenishment, transportation, and capacity decisions. Moreover, the multifunctional role of bio-hubs as processing, storage, and synchronization nodes

introduces additional coordination challenges that cannot be effectively captured by traditional deterministic or single-level optimization models.

This study addresses the coordination problem in a bi-level BSC network including suppliers, intermediary bio-hubs, and remote power plants operating under uncertainty. Bio-hubs act as central decision-makers by selecting suppliers with sufficient feedstock availability at competitive prices, processing orders, and planning wood pellet production to improve feedstock quality while simultaneously coordinating multimodal transportation. Trucks are used year-round to collect feedstock from suppliers, whereas ships are the only mode available to deliver biomass to remote power plants during restricted seasonal windows. Since access to these communities is limited, power plants must place orders in advance and maintain enough inventory to ensure uninterrupted electricity generation throughout inaccessible periods, while minimizing the inventory cost. The challenge is compounded by the limited fleet resources, which necessitate efficient allocation to minimize transportation costs and the number of trips. It is further intensified by multiple sources of uncertainty, including variability in feedstock quality, stochastic production yields, and transportation delays. Therefore, coordination and information sharing are applied across all tiers of the proposed BSC network to align inventory, production, and transportation planning, while systematically accounting for these sources of uncertainty. By reducing redundancies and improving cohesion among decision-makers, it contributes to higher resource utilization while minimizing the overall system cost.

6.3. Model Description

The current study develops a derivative-free optimization (DFO) framework, building on ABS, to address the coordination of tactical and operational decisions within the proposed BSC under uncertainty. This approach facilitates the optimization of decision variables in settings where traditional derivative-based methods are impractical or infeasible and operates as a form of black-box optimization (Stripinis et al., 2024). Unlike traditional optimization techniques that require gradients, DFO iteratively explores the solution space by evaluating candidate points and the corresponding objective function and using this information to progressively narrow the search region toward optimal or near-optimal solutions without requiring gradient information. Figure 6.1 illustrates the overall architecture and sequential implementation steps of the proposed framework. The process begins with constructing a detailed simulation model of the multi-echelon BSC network. Unlike traditional mathematical formulations, the interactions among the SC entities are modeled as autonomous agents, each governed by a set of behavioral rules and are accessible through the central agent. These rules encode the

operational logic of each agent and specify how it executes its primary functions (e.g., inventory management, production planning, and transportation coordination) and how it communicates and coordinates with other agents across the network. By embedding these decision-making rules, the simulation captures dynamic interdependencies, cascading effects, and stochastic variations across SC tiers, enabling a realistic representation of operational behavior under uncertainty. This model is proposed considering the following assumptions:

- The demand is known over the planning horizon.
- The probability distribution of uncertain parameters is known.
- The model is developed considering multiple periods.
- Bio-hubs are the main coordination drivers within the BSC network.
- No suppliers have been already selected.
- The capacity of suppliers and storage space of bio-hubs are limited.

6.3.1. Agents' Communication Rules

According to Figure 6.1, there are five main agents, each of which are the main entities of the BSC. To clarify the communication rules of these agents, following discusses each agent's main algorithms and operations.

1) Supplier: In the proposed ABS model, the supplier agent represents the production of raw biomass feedstock, characterized by key quality attributes such as moisture content and heating value. These attributes are modeled through probabilistic distributions to capture inherent variability and uncertainty. Suppliers operate within predefined working hours and continuously monitor incoming orders. Upon receiving an order, the supplier selects the most suitable truck type based on fleet capacity and then sends the order information (i.e., receiver ID, order amount and feedstock quality) to the *Truck* agent. This rule prevents underutilization of vehicle capacity, which reduces unnecessary trips and limits the increase in per-unit transportation costs.

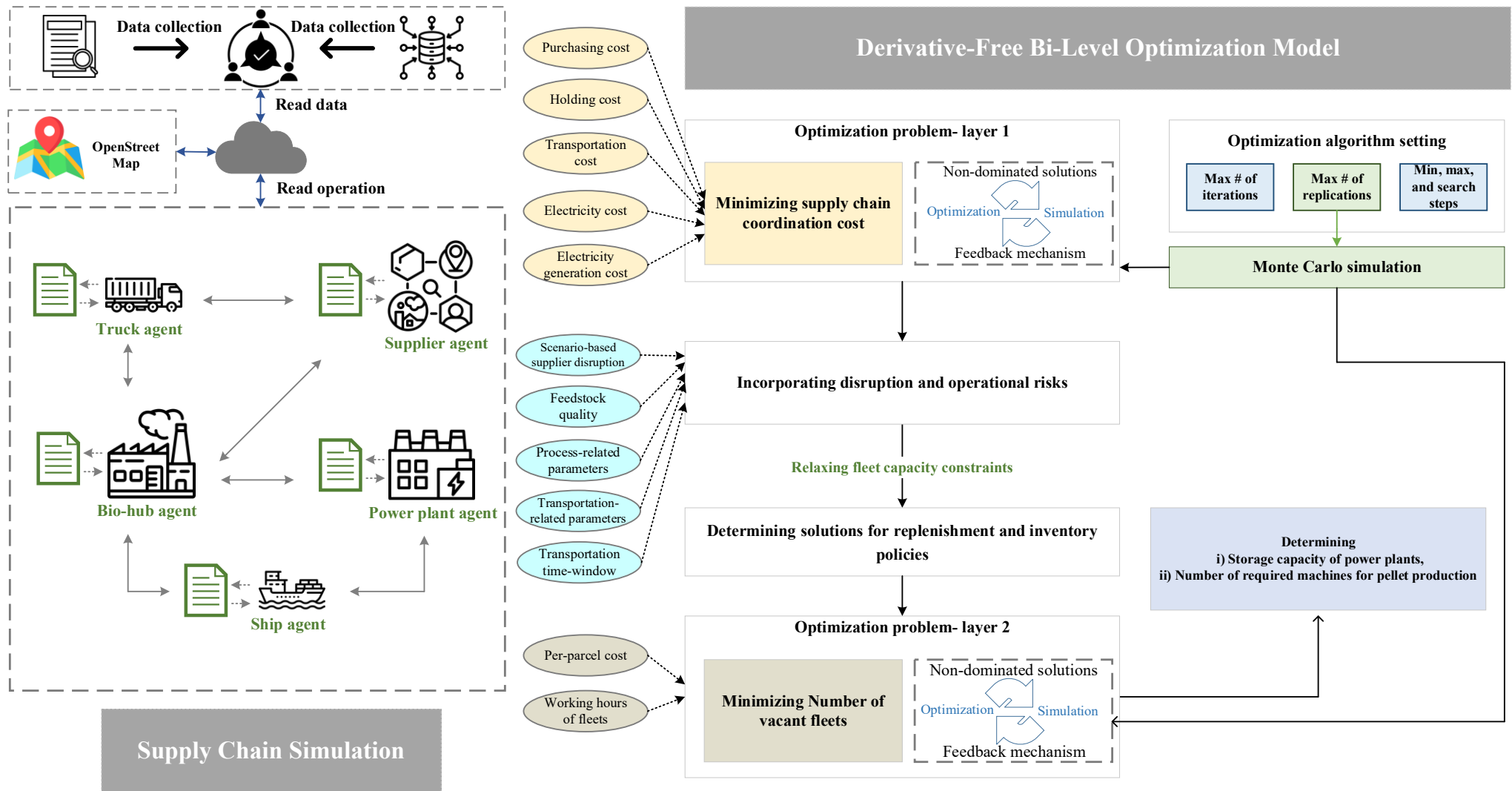


Figure 6.1. The proposed methodology to address the coordinated SC and logistics decisions

The dispatching process within the supplier agent is implemented through a combination of collections, an event, and a function. Specifically, the “*order checking*” event identifies which bio-hub has placed an order and the corresponding order quantity. Once the demand is established, the agent queries the pool of trucks currently in a ready state that are associated with the requesting bio-hub. For all available vehicles, the “*truck finder*” function evaluates the absolute difference between the order quantity and truck capacity. The truck with the minimum deviation is then selected for dispatch to ensure efficient load utilization while minimizing partial loads and reducing unnecessary trips. This logic formalizes the decision-making process and directly links order fulfillment to dynamic fleet allocation under operational constraints. Algorithms 6.1 and 6.2 show the event and function, respectively.

Algorithm 6.1. “*Order Checking*” event

```

If (getHourOfDay() >= main.supplierTransportStartShift && getHourOfDay() <=
main.supplierTransportFinishShift)
    If (orderReceivedAmount.size() > 0 && orderReceivedAmount.get(0) != 0)
        temp.clear();
        temp1.clear();
        Truck = truckFinder(orderReceivedAmount.get(0), orderReceivedHub.get(0));
        If (Truck != null)
            If (orderReceivedAmount.get(0) > Truck.capacity)
                If (totalProduction >= Truck.capacity)
                    totalProduction -= Truck.capacity;
                    orderInHand -= Truck.capacity;
                    Truck.destination = this.getIndex();
                    Truck.biomassAmount = Truck.capacity;
                    Truck.orderTime = orderReceivedTime.get(0);
                    Truck.moistureContent = moistureContent;
                    Truck.heatingValue = heatingValue;
                    orderReceivedAmount.set(0, orderReceivedAmount.get(0)-
Truck.capacity);
                    Send ("move", Truck);
                    If (orderReceivedAmount.get(0)==0)
                        orderReceivedAmount.remove(0);
                        orderReceivedHub.remove(0);
                        orderReceivedTime.remove(0);
                Else
                    If (totalProduction >= orderReceivedAmount.get(0))
                        totalCost += (price * orderReceivedAmount.get(0));
                        main.totalCostSupplyChain += (price *
orderReceivedAmount.get(0));
                        totalProduction -= orderReceivedAmount.get(0);
                        orderInHand -= orderReceivedAmount.get(0);
                    Truck.destination = this.getIndex();
                    Truck.biomassAmount = orderReceivedAmount.get(0);
                    Truck.orderTime = orderReceivedTime.get(0);
                    Truck.moistureContent = moistureContent;
                    Truck.heatingValue = heatingValue;
                    Send ("move", Truck);
                    orderReceivedAmount.remove(0);
                    orderReceivedHub.remove(0);
                    orderReceivedTime.remove(0);
            Else

```

```

        If (orderReceivedAmount.size() > 0 && orderReceivedAmount.get(0) == 0)
        {
            orderReceivedAmount.remove(0);
            orderReceivedHub.remove(0);
            orderReceivedTime.remove(0);
        }
    End

```

Algorithm 6.2. “*Truck finder*” function

```

For bio-hub [i]  $\forall i \in \{1, 2, \dots, n\}$ 
    For (int ii=0; ii<main.trucks.size(); ii++)
        If (main.trucks.get(ii).from == 0)
            If (main.trucks.get(ii).inState(truck.ready))
                temp.add(main.trucks.get(ii).capacity);
                temp1.add(main.trucks.get(ii));
                If (temp.size() > 0)
                    If (temp.size() == 1)
                        return temp1.get(0);
                    Else
                        double diff = 100000000;
                        int index = -1;
                        For (int jj=1 ; jj<temp.size(); jj++)
                            If (abs (biomassAmount - temp1.get(jj).capacity) < diff)
                                index = jj;
                                diff = biomassAmount - temp1.get(jj).capacity;
                        return temp1.get(index);
            return null;
    End

```

II) Bio-Hub: The bio-hub agent plays a central coordinating role within the proposed BSC by linking spatially distributed suppliers with geographically dispersed demand nodes. Functioning as a multi-purpose facility, the bio-hub is responsible for wood pellet production, managing both inbound and outbound orders, and dispatching a multimodal fleet (i.e., trucks and ships). The pellet production process is executed sequentially through a series of unit operations, including drying, grinding, pelletizing, and cooling. In the drying stage, a fraction of the received feedstock is combusted to generate the thermal energy required to reduce the moisture content of the remaining feedstock to a target level and consequently, improve its energy quality and downstream usability (Mobini et al., 2014). The overall modeling components of this agent such as parameters, production line specifications, collection entities, state variables, functions, and events, are shown in Figure 6.2.

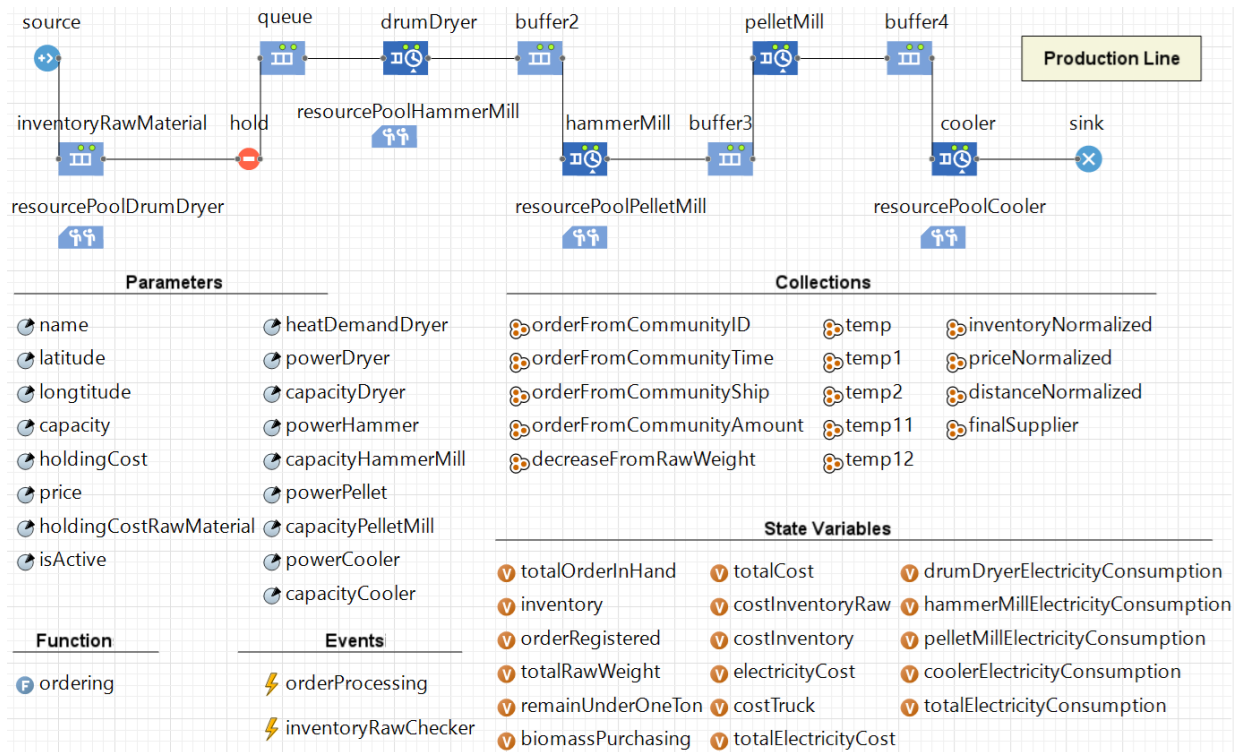


Figure 6.2. Modeling interface of bio-hub node in Anylogic with all associated components

Inventory management at the bio-hub follows an (s, S) policy, where a replenishment order is triggered once the available inventory, including work-in-progress along the production line, falls below the reorder point (s). At this stage, the “*Inventory Raw Checking*” event (Algorithm 6.3) is activated, which initiates the “*Ordering*” function (Algorithm 6.4). This function evaluates candidate suppliers by assessing available feedstock quantities, unit prices, and transportation distances. These indicators are used to rank potential suppliers and select the most suitable option. The order details are then transmitted to the corresponding supplier agent, to ensure systematic coordination across the network. To satisfy the demand of destination nodes, the “*Order Processing*” event continuously monitors incoming requests and verifies inventory availability at bio-hubs. Whenever the transportation time window becomes accessible, and sufficient inventory is available, the event triggers the dispatch process by transmitting detailed order information (including receiver identification, dispatch time, and shipment quantity) to the ship agent. This mechanism ensures that shipment scheduling is synchronized with both inventory levels and temporal accessibility constraints. This event also triggers a temporary halt in the production line when the sum of on-hand inventory and work-in-progress materials exceeds the facility’s storage capacity.

Algorithm 6.3. “Inventory Raw checking” event

```
For bio-hub [i]  $\forall i \in \{1, 2, \dots, n\}$ 
    If bio-hub [i] is active==1
        If (((inventory + buffer2.size() + buffer3.size()+ buffer4.size() +
            drumDryer.queueSize() + drumDryer.delaySize() +
            hammerMill.queueSize() + hammerMill.delaySize() +
            pelletMill.queueSize() + pelletMill.delaySize() + cooler.queueSize() +
            cooler.delaySize()) < main.sLevelHub[i]) && orderRegistered == 0)
            double amount = main.SSLevelHub[i] - (inventory + buffer2.size() +
                buffer3.size() + buffer4.size() + drumDryer.queueSize() +
                drumDryer.delaySize() + hammerMill.queueSize() +
                hammerMill.delaySize()+ pelletMill.queueSize() + pelletMill.delaySize() +
                cooler.queueSize() + cooler.delaySize());
            amount = amount;
            int temp = (int) amount;
            temp = temp;
            orderRegistered = temp;
            ordering (amount);
End
```

Algorithm 6.4. “Ordering” function

```
amount = (int) amount / main.biohubToSupplierBatchOrder;
amount = Math.round(amount);
For (int jj=0; jj<main.biohubToSupplierBatchOrder; jj++)
    temp.clear();
    temp1.clear();
    temp2.clear();
    inventoryNormalized.clear();
    priceNormalized.clear();
    distanceNormalized.clear();
    finalSupplier.clear();
    For (int ii=0; ii<main.suppliers.size(); ii++)
        temp.add(main.suppliers.get(ii).totalProduction-
            main.suppliers.get(ii).orderInHand);
        temp1.add(main.suppliers.get(ii).price);
        For bio-hub [i]  $\forall i \in \{1, 2, \dots, n\}$ 
            temp2.add(main.suppliers.get(ii).distanceToHub [i]);

    double minInv = min(temp, t->t.doubleValue());
    double maxInv = max(temp, t->t.doubleValue());
    double minP = min(temp1, t->t.doubleValue());
    double maxP = max(temp1, t->t.doubleValue());
    double minM = min(temp2, t->t.doubleValue());
    double maxM = max(temp2, t->t.doubleValue());

    For (int ii=0; ii<main.suppliers.size(); ii++)
        inventoryNormalized.add(((temp.get(ii) - minInv)/(maxInv - minInv) >=0 ?
(temp.get(ii) - minInv)/(maxInv - minInv) : 0 ));
        priceNormalized.add(((temp1.get(ii) - minP) / (maxP - minP)));
        distanceNormalized.add(((temp2.get(ii) - minD) / (maxD - minD)));

    For (int ii=0; ii<main.suppliers.size(); ii++)
        finalSupplier.add (w1*inventoryNormalized.get(ii)-
w2*priceNormalized.get(ii)-0*moistureNormalized.get(ii)-
w3*distanceNormalized.get(ii));
```

```

double finalValue = max(finalSupplier, t->t.doubleValue());
int which = finalSupplier.indexOf(finalValue);

main.suppliers.get(which).orderReceivedAmount.add(amount);
main.suppliers.get(which).orderReceivedHub.add(this.getIndex());
main.suppliers.get(which).orderReceivedTime.add(time());
main.suppliers.get(which).orderInHand += amount;
biomassPurchasing += main.suppliers.get(which).price * amount * (1-
    main.suppliers.get(which).moistureContent);
totalCost += main.suppliers.get(which).price * amount * (1-
    main.suppliers.get(which).moistureContent);

```

End

III) Demand Nodes:

This node represents the biomass-based power generation facility, which is responsible for converting stored feedstock into electricity. Each node is characterized by a predetermined electricity generation capacity U_j , a biomass-to-electricity conversion rate β_j and a loading factor γ_j which reflects the actual operational utilization of the installed capacity. The facility also maintains an inventory of feedstock to ensure continuous electricity production within its technical and operational limits. To satisfy the hourly electricity demand D_j at each demand node j , the electricity generated from biomass w_j must meet the following operational constraint: the $w_j \leq \text{Min}(U_j * \gamma_j, D_j)$. This ensures that the generation output does not exceed either the effective generation capacity or the actual demand requirement. The quantity of biomass consumed to produce w_j is determined by the conversion efficiency, expressed as $B_j = w_j / \beta_j$. The total cost of electricity generation at node j is computed based on the levelized cost of electricity from biomass, which integrates both capital and operational expenditures over the plant's lifetime.

This node is authorized to place replenishment orders on a monthly basis, constrained by the operational availability of transportation routes within the designated open shipping window. The ordering strategy is designed to ensure sufficient feedstock availability throughout the subsequent closed transportation period, when delivery operations are not feasible due to seasonal disruptions (e.g., ice formation or road closures). Accordingly, the node evaluates its inventory position and demand forecast over the entire non-operational period to determine the optimal order quantity within the available shipping window. This proactive replenishment mechanism guarantees that inventory levels remain adequate to sustain continuous operations during isolation periods, while minimizing holding and stockout risks under uncertain demand and transportation conditions. The aggregate quantity ordered within the open window must satisfy the total projected demand. Any supply shortfall would lead to prolonged power outages

for remote communities, which pose severe risks to energy reliability, operational continuity, and community resilience. This condition is incorporated as a constraint within the optimization model.

IV) Transportation Agents: Within the proposed network, multiple transportation fleets with heterogeneous capacities and cost structures are managed by the bio-hubs. Depending on the seasonal accessibility of transportation routes, these fleets including trucks and ships are dynamically dispatched to transport feedstock from suppliers to bio-hubs and subsequently to downstream demand nodes. Upon returning to the bio-hubs, inventory records for both the supplying and receiving entities are updated to reflect the actual material flow. To capture the temporal evolution of transportation activities, several transition states are defined to represent key operational stages, including loading, in-transit movement, unloading, and return trips. Figure 6.3 presents the statechart of the truck and ship modules, along with their associated state variables that govern state transitions. Within these modules, parameters such as loading and unloading times, travel speed, and fuel consumption are modeled as stochastic variables following specified probability distributions to reflect real-world variability and uncertainty in transportation performance.

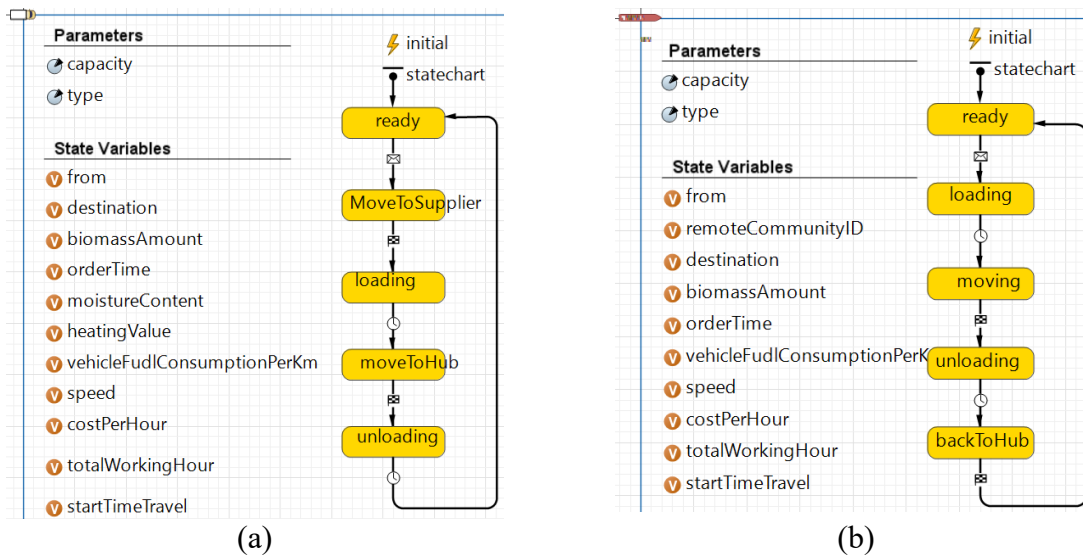


Figure 6.3. Statechart of fleet behavior and transportation process flow

V) Coordination Mechanism: To determine which bio-hub is responsible for fulfilling the orders of destination nodes, a coordination mechanism is implemented to enable systematic information sharing among hubs. This mechanism is triggered by the “*Order Dispatch*” event, which is managed by the central agent. Once activated, the mechanism generates a list of available heterogeneous ships in a ready state at each hub. The dispatching process is then executed

through the “*Dispatch*” function, where the per-parcel shipping cost is calculated for each candidate vessel as a function of ship capacity, cost and the size of the received order. This formulation leverages economies of scale by allocating larger orders to higher-capacity ships and consequently reduces the number of trips, lowers transportation costs, and minimizes associated CO₂ emissions. Following this evaluation, the bio-hub with the most appropriate vessel is selected for order execution. The mechanism iteratively updates the availability of ships and order status until all orders are dispatched or no further vessels are available. The detailed implementation of the “*Order Dispatch*” event and “*Dispatch*” function is presented in Algorithms 6.5 and 6.6, respectively.

Algorithm 6.5. “*Order Dispatch*” event

```

For bio-hub [i]  $\forall i \in \{1, 2, \dots, n\}$ 
  freeFleetHub[i].clear();

For (int ii=0; ii<ships.size(); ii++)
  If (ships.get(ii).inState(ship.ready))
    For bio-hub [i]  $\forall i \in \{1, 2, \dots, n\}$ 
      freeFleetHub[i].add(ships.get(ii));

If (bioHubShareDemandRCAmount.size() > 0 && (freeFleetHub[i].size() > 0))
  double remain = 0;
  For (int ii=0; ii<bioHubShareDemandRCAmount.size(); ii++)
    remain=functionDispatch(bioHubShareDemandRCAmount.get(ii),
      bioHubShareDemandRCID.get(ii), bioHubShareDemandRCTime.get(ii));
    bioHubShareDemandRCAmount.set(ii, remain);
    For bio-hub [i]  $\forall i \in \{1, 2, \dots, n\}$ 
      If (freeFleetHub [i].size() ==0)
        break;

  For (int ii=0; ii<bioHubShareDemandRCAmount.size(); ii++)
    If (bioHubShareDemandRCAmount.get(ii) == 0)

      bioHubShareDemandRCAmount.remove(ii);
      bioHubShareDemandRCID.remove(ii);
      bioHubShareDemandRCTime.remove(ii);
      ii--;

End

```

Algorithm 6.6. “Dispatch” function

```
double cost = 0;
double partial = 0;
int indexMin = -1;
int hubMin = -1;
While (amount > 0)
    double globalMinCost = -1;
    For (int h = 0; h < biohubs.size(); h++)
        ArrayList<Ship> freeFleet = freeFleetHubs.get(h); // fleet of hub h
        ArrayList<Double> pricePerKGFleet = pricePerKGFleetHubs.get(h);
        pricePerKGFleet.clear();
        If (freeFleet.size() > 0)
            For (int ii = 0; ii < freeFleet.size(); ii++)
                partial = Math.min(amount, freeFleet.get(ii).capacity);
                cost = (HubKMTToRC[h].get(RC) / freeFleet.get(ii).speed) *
                    freeFleet.get(ii).costPerHour;
                pricePerKGFleet.add(cost / partial);
                double minCostHub = Collections.min(pricePerKGFleet);

        If (globalMinCost == -1 || minCostHub < globalMinCost) {
            globalMinCost = minCostHub;
            hubMin = h;
            indexMin = pricePerKGFleet.indexOf(minCostHub);

        If (globalMinCost == -1) break;

    Ship selectedShip = freeFleetHubs.get(hubMin).get(indexMin);
    partial = Math.min(amount, selectedShip.capacity);
    costUpdaterDispatch(RC, hubMin, partial);
    biohubs.get(hubMin).orderFromCommunityAmount.add(partial);
    biohubs.get(hubMin).orderFromCommunityID.add(RC);
    biohubs.get(hubMin).orderFromCommunityTime.add(timeRC);
    biohubs.get(hubMin).orderFromCommunityShip.add(selectedShip);

    freeFleetHubs.get(hubMin).remove(indexMin);

    amount -= partial;
    return amount;
End
```

IV) Scenario-based Disruption Modeling:

In this study a scenario-based modeling is employed to capture the impact of discrete disruption events that may affect the SC network. This approach evaluates a set of scenarios, where each scenario $m \in M$ represents a unique configuration of potential SC disruption. These scenarios are generated by considering all possible combinations of node availability and failure states. For each scenario m , a probability of occurrence τ_m is assigned to reflect the likelihood of that disruption pattern. This probability is computed using the following equation, based on the distinction between operational and disrupted nodes. The total number of scenarios, expressed

as $M = |2^{R^r}|$ corresponds to the power set of possible disruption combinations, where each specific disruption scenario $m \in M$ belongs to a subset of disrupted nodes $R_m^r \subset R^r$. Each node r is associated with an independent disruption probability Φ_r , representing the likelihood of its failure within the network. The disruption probability of unreliable node $r \in R^r$ is independent of others (Asghari et al., 2025). Accordingly, the disruption probability of occurrence for scenario r , denoted as τ_m , is computed as $\tau_m = \prod_{r \in R_m^r} \Phi_r * \prod_{r \notin R_m^r} (1 - \Phi_r)$. This equation quantifies the overall probability of each scenario by accounting for both disrupted and undisrupted nodes. This formulation enables a probabilistic representation of disruptions without assuming an “all-or-nothing” behavior to capture a richer and more realistic spectrum of SC risk scenarios. In fact, it expresses the remaining capacity of node r in scenario m as a fractional value. To make this equation clearer, Table 6.1 provides a disruption scenario list for a small instance including $S_r, r=1, \dots, 5$. To implement this behavior in the simulation model, the value of τ_m calculated for each node (e.g., supplier), is used in “Roulette” function to calculate the CDF shown in algorithm 6.7.

Table 6.1. Boolean matrix of nodes status across disruption scenarios (0 = operational, 1 = disrupted)

	Nodes						Nodes					
	S_1	S_2	S_3	S_4	S_5		S_1	S_2	S_3	S_4	S_5	
Disruption scenario	m_1	0	0	0	0	0	m_{17}	1	1	1	0	0
	m_2	1	0	0	0	0	m_{18}	1	1	0	1	0
	m_3	0	1	0	0	0	m_{19}	1	1	0	0	1
	m_4	0	0	1	0	0	m_{20}	1	0	1	1	0
	m_5	0	0	0	1	0	m_{21}	1	0	1	0	1
	m_6	0	0	0	0	1	m_{22}	1	0	0	1	1
	m_7	1	1	0	0	0	m_{23}	0	1	1	1	0
	m_8	1	0	1	0	0	m_{24}	0	1	1	0	1
	m_9	1	0	0	1	0	m_{25}	0	1	0	1	1
	m_{10}	1	0	0	0	1	m_{26}	0	0	1	1	1
	m_{11}	0	1	1	0	0	m_{27}	1	1	1	1	0
	m_{12}	0	1	0	1	0	m_{28}	0	1	1	1	1
	m_{13}	0	1	0	0	1	m_{29}	1	1	1	0	1
	m_{14}	0	0	1	1	0	m_{30}	1	0	1	1	1
	m_{15}	0	0	1	0	1	m_{31}	1	1	0	1	1
	m_{16}	0	0	0	1	1	m_{32}	1	1	1	1	1

Algorithm 6.7. “Roulette” function

```

disruptionProbabilityCDF.add(disruptionProbability.get(0));
For (int ii=1; ii<disruptionProbability.size(); ii++)
    disruptionProbabilityCDF.add (disruptionProbabilityCDF.get(ii-
1)+disruptionProbability.get(ii));
double num = uniform (0, disruptionProbabilityCDF.get (disruptionProbabilityCDF.size()-
1));

For (int ii=0; ii<disruptionProbabilityCDF.size(); ii++)
    If (num >= disruptionProbabilityCDF.get(ii) &&
        num<disruptionProbabilityCDF.get(ii+1))
        return ii;
return 0;
End

```

It is worth mentioning that in AnyLogic, a “Roulette” is a probabilistic selection mechanism that enables the model to choose one alternative from a set of options based on predefined weights or probabilities. It is commonly employed to represent stochastic decision-making processes, where each option is assigned a probability proportional to its likelihood of being selected. The function returns a single outcome per execution, facilitating the modeling of randomness in agent behaviors, process flows, or scenario branching within simulation environments. Two events, “*Disruption Organizer*” and “*Disruption Occurrence*” are defined to operationalize the disruption scenarios within the model. The first event schedules and manages the timing and sequence of potential disruptions, while the second one executes the actual impact on the affected nodes, which enables the simulation of dynamic, stochastic disruption patterns. The main components of disruption modeling are presented in Figure 6.4 and are accessible through the central agent. Algorithm 6.8 presents the extended closed-form representation of the dynamic “*Disruption Occurrence*” event for a scenario involving five affected suppliers.

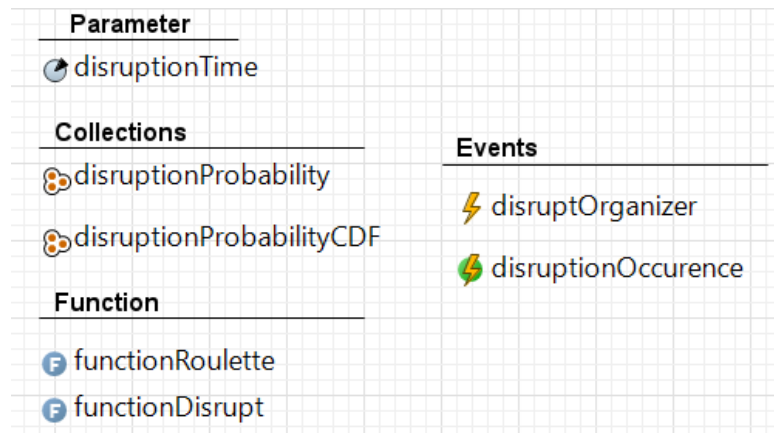


Figure 6.4. Components of disruption modeling controlled by the central agent.

Algorithm 6.8. “*Disruption Occurrence*” event

```
If (whichSupplier1 != -1)
    suppliers.get(whichSupplier1-1).capacity = uniform(suppliers.get(whichSupplier1-1).capacity* w1, suppliers.get(whichSupplier1-1).capacity* w2);
    suppliers.get(whichSupplier1-1).minCapacity = uniform(suppliers.get(whichSupplier1-1).minCapacity* w1, suppliers.get(whichSupplier1-1).minCapacity* w2);
    suppliers.get(whichSupplier1-1).maxCapacity = uniform(suppliers.get(whichSupplier1-1).maxCapacity* w1, suppliers.get(whichSupplier1-1).maxCapacity* w2);

If (whichSupplier2 != -1)
    suppliers.get(whichSupplier2-1).capacity = uniform(suppliers.get(whichSupplier2-1).capacity* w1, suppliers.get(whichSupplier2-1).capacity* w2);
    suppliers.get(whichSupplier2-1).minCapacity = uniform(suppliers.get(whichSupplier2-1).minCapacity* w1, suppliers.get(whichSupplier2-1).minCapacity* w2);
    suppliers.get(whichSupplier2-1).maxCapacity = uniform(suppliers.get(whichSupplier2-1).maxCapacity* w1, suppliers.get(whichSupplier2-1).maxCapacity* w2);

If (whichSupplier3 != -1)
    suppliers.get(whichSupplier3-1).capacity = uniform(suppliers.get(whichSupplier3-1).capacity* w1, suppliers.get(whichSupplier3-1).capacity* w2);
    suppliers.get(whichSupplier3-1).minCapacity = uniform(suppliers.get(whichSupplier3-1).minCapacity* w1, suppliers.get(whichSupplier3-1).minCapacity* w2);
    suppliers.get(whichSupplier3-1).maxCapacity = uniform(suppliers.get(whichSupplier3-1).maxCapacity* w1, suppliers.get(whichSupplier3-1).maxCapacity* w2);

If (whichSupplier4 != -1)
    suppliers.get(whichSupplier4-1).capacity = uniform(suppliers.get(whichSupplier4-1).capacity* w1, suppliers.get(whichSupplier4-1).capacity* w2);
    suppliers.get(whichSupplier4-1).minCapacity = uniform(suppliers.get(whichSupplier4-1).minCapacity* w1, suppliers.get(whichSupplier4-1).minCapacity* w2);
    suppliers.get(whichSupplier4-1).maxCapacity = uniform(suppliers.get(whichSupplier4-1).maxCapacity* w1, suppliers.get(whichSupplier4-1).maxCapacity* w2);

If (whichSupplier5 != -1)
    suppliers.get(whichSupplier5-1).capacity = uniform(suppliers.get(whichSupplier5-1).capacity* w1, suppliers.get(whichSupplier5-1).capacity* w2);
    suppliers.get(whichSupplier5-1).minCapacity = uniform(suppliers.get(whichSupplier5-1).minCapacity* w1, suppliers.get(whichSupplier5-1).minCapacity* w2);
    suppliers.get(whichSupplier5-1).maxCapacity = uniform(suppliers.get(whichSupplier5-1).maxCapacity* w1, suppliers.get(whichSupplier5-1).maxCapacity* w2);
```

End

6.3.2. Simulation-based Optimization

After defining simulation modules, the framework formulates a bi-level optimization problem to identify optimal decision variables. The first optimization layer considers reorder points s_i and target inventory levels S_i , $\forall i \in I$ at each intermediary node, along with replenishment quantities Q_{jt} , $\forall j \in J, \forall t \in T$ for each demand node as decision variable. To avoid excessive replenishment costs and multiple fleet dispatches, each demand node is constrained to issue at most one order per month (t), consistent with the transportation time window. Multimodal fleet availability is assumed unrestricted at this layer. A genetic algorithm (GA) is employed as the DFO solver to explore the solution space. This algorithm evaluates the objective function, which aggregates total network costs, including procurement costs at intermediary and demand nodes, transportation costs (truck and ship), electricity consumption at intermediary nodes, inventory holding costs at intermediary and demand nodes, and electricity generation costs. Within each GA iteration, the simulation model provides system-level feedback, while capturing nonlinear dynamics and interdependencies among network entities. Additionally, Monte Carlo replications are nested to quantify stochastic variability in operational parameters (e.g., loading/unloading times, machinery delays, and feedstock quality), enabling assessment of solution robustness under uncertainty. This integrated approach allows optimization of network-wide decisions while accounting for dynamic, stochastic, and interdependent behaviors inherent in BSCs.

In the second optimization layer, the decision variables obtained from the first layer are treated as fixed parameters. Building on these values, the second layer determines the optimal fleet composition at each intermediary node. Specifically, it identifies the number of fleets of each type with capacity $c \in C$ assigned to intermediary node $i \in I$, represented by decision variable z_{ic} . This decision structure enables the model to capture the heterogeneity of transportation assets and their operational trade-offs across the multimodal network. The objective of this layer is twofold: (i) to minimize the number of idle or underutilized fleets (i.e., vehicles with zero or partial operational load), and (ii) to reduce the total operational cost of the system. Accordingly, the fitness function integrates both utilization efficiency and cost performance, expressed in terms of the total idle working hours across all fleets in the system. This formulation ensures that fleet allocation decisions are not only cost-effective but also operationally efficient in terms of resource deployment and service reliability. Alongside these decision variables, a set of state variables are dynamically computed to evaluate system performance. These include the CO₂ emissions associated with truck and ship operations, the electricity consumption at intermediary nodes, the quantity of feedstock transported to both

intermediary and demand nodes, the number of transportation trips, and the detailed cost components of network operation. These state variables are endogenously updated within the simulation environment based on the decisions made in each iteration, providing a comprehensive performance profile that links operational decisions to environmental and economic outcomes.

6.4. Results and Discussions

6.4.1. Case Descriptions

To demonstrate the framework's applicability, the proposed BSC network is implemented for nine remote, off-grid Inuit communities in Northern Quebec, including Kangiqsujaq, Salluit, Ivujivik, Kuujuaq, Inukjuak, Puvirnituk, Kangiqsualujuaq, Akulivik, and Kuujuarapik. These communities currently rely predominantly on diesel as their main energy source due to limited grid connectivity, severe climatic conditions, and the high logistical costs associated with fuel transportation and storage. The network architecture comprises a set of potential biomass suppliers distributed across the southern region, two strategically located bio-hubs serving as intermediate processing and storage facilities, and local power plants within each community. These power plants are designed to generate electricity from biomass-derived feedstock, supported by dedicated storage systems to manage seasonal variability and ensure year-round supply reliability. The multi-echelon configuration captures the interactions among suppliers, bio-hubs, and community-level energy systems to enable coordinated logistics, inventory, and replenishment planning under stochastic conditions. By operationalizing this network, the study aims to evaluate the economic and environmental benefits of transitioning from diesel-based to biomass-based electricity generation, emphasizing the reduction of greenhouse gas emissions, enhancement of energy security, and development of a self-sufficient renewable energy system tailored to northern off-grid conditions. The complete input data for the baseline BSC network is presented in Chapter 5 under the BSC network simulation subsection.

6.4.2. Analysis of the Results

6.4.2.1. Replenishment Decisions

In this section, the results derived from the bi-level optimization framework are presented and analyzed. The objective is to investigate the sourcing strategies and order allocation decisions within the supply network in the presence of risk factors. The entire framework was implemented and executed in AnyLogic 8.9.5 PLE, simulating a one-year operational horizon under 10,000 iterations and 500 replications. This study proposes six suppliers with 0.4, 0.3, 0.5, 0.55, 0.45,

and 0.25 disruption probability, respectively. Given that the transportation routes to remote communities are accessible for only six months due to seasonal constraints, order placement is restricted to this period. Figure 6.5 illustrates the monthly biomass order allocations across the communities, highlighting the distinction between low-demand communities ($j=1, 3, 6, 7$) and high-demand communities ($j=2, 4, 5, 8, 9$), with high-demand nodes consistently requiring two to five times more biomass. In the first months of the simulation (May and June), orders are moderate as shipments are initiated using available heterogeneous ships with varying capacities to ensure deliveries fit within the May-October transportation window. In the last months of the open window (September and October), order quantities increase again, particularly for low-demand communities to secure sufficient biomass before deliveries cease for the winter. The heterogeneity of the shipping fleet influences both the timing and size of shipments, which allows larger vessels to efficiently serve high-demand nodes while smaller ships provide flexible deliveries to low-demand communities. Overall, these trends demonstrate how temporal demand fluctuations, seasonal transportation constraints, and fleet heterogeneity collectively shape sourcing strategies, shipment scheduling, and order allocation to ensure a reliable, cost-effective, and risk-aware biomass supply network over the operational horizon.

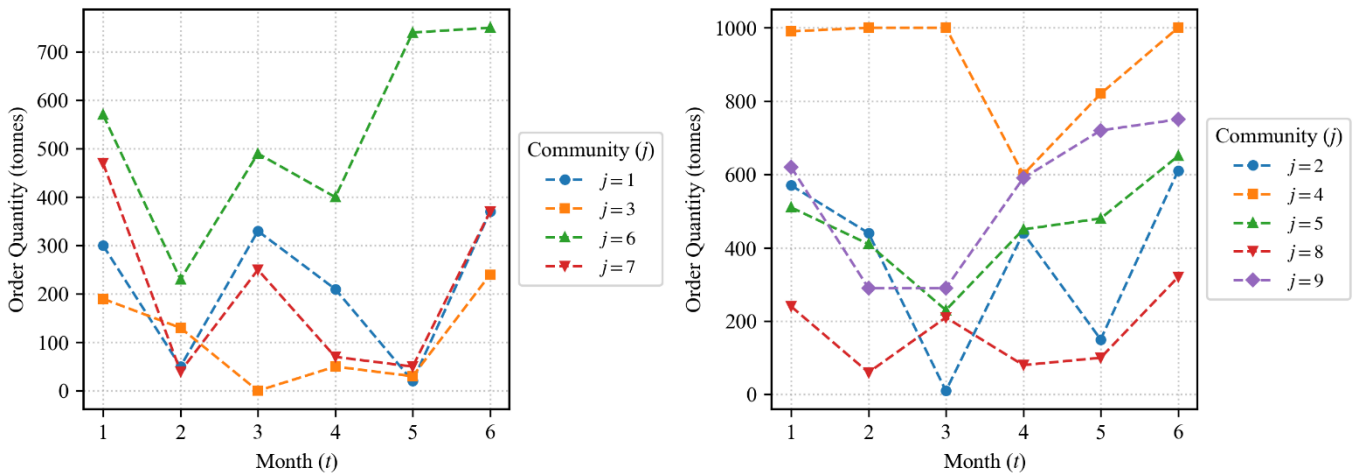


Figure 6.5. Order allocation across communities over planning horizon t

To evaluate the operational performance of the bio-hubs within the BSC network, the hub-level shipment outputs were analyzed in the context of inventory management and heterogeneous fleet deployment. Both hubs implement a daily order-up-to inventory policy (s, S), which triggers replenishment whenever inventory falls below the hub-specific reorder point (s) to maintain continuous responsiveness to dynamic community demand. According to the DFO findings, hub $i=1$ operates with a $s_1=200$ tonne and $S_1=295$ tonne, while hub $i=2$ is specified with

$s_2=120$ tonne and $S_2=195$ tonne. As shown in Figure 6.6, first hub emerges as the primary supplier for high-demand communities, delivering the largest cumulative volumes to nodes such as $j=4$, $j=5$, and $j=9$, while simultaneously providing substantial allocations to low-demand nodes like $j=6$ and $j=7$. The second hub, as a supportive hub, distributes biomass more evenly across both low- and high-demand communities to ensure baseline supply is maintained network-wide.

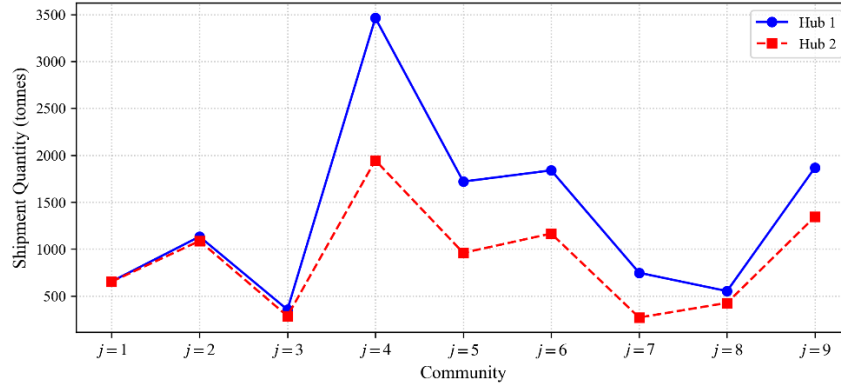


Figure 6.6. Hub-level biomass shipments to communities

In fact, the closer proximity of the first hub to the majority of communities allows vessels to complete deliveries and return trips more rapidly which increases the effective utilization of heterogeneous ships. Shipments are systematically allocated according to vessel capacity to optimize fleet utilization, leverage economies of scale, reduce transportation costs, and minimize associated CO₂ emissions. Collectively, these findings underscore how hub capacity, spatial positioning, inventory control policies, and fleet heterogeneity interact synergistically to produce an efficient distribution strategy and ensure reliable biomass supply to all communities. To support these findings, Figure 6.7 illustrates the temporal inventory profiles of both bio-hubs operating under a daily (s, S) policy. The first hub exhibits frequent replenishment cycles due to rapid inventory depletion driven by high demand. The tight gap between order placement and recovery reflects its role as the primary distribution hub. Conversely, second hub shows more stable inventory levels and less frequent ordering, consistent with its supportive role in maintaining baseline supply across the network. After the closure of the operational time window, inventory levels in both hubs stabilize near their respective upper thresholds, indicating the termination of outbound shipments and the restoration of stock levels.

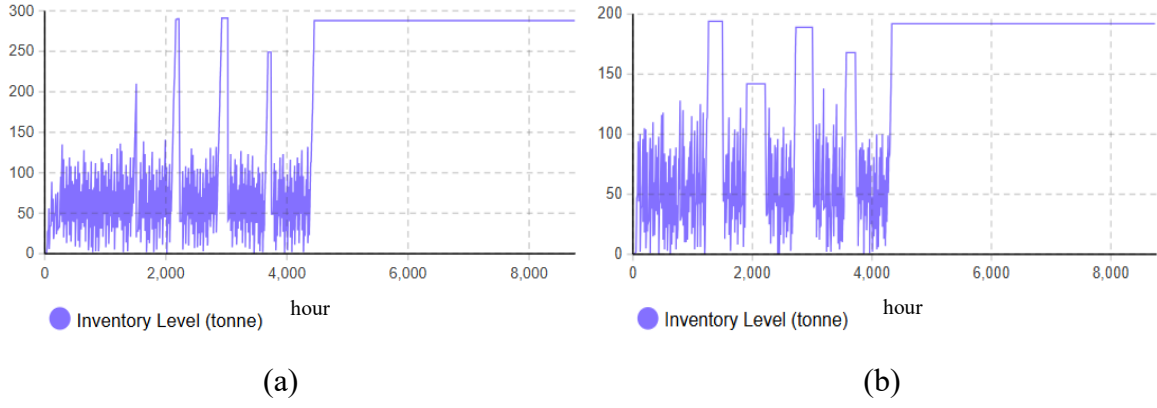


Figure 6.7. Dynamic behaviour of bio-hubs across planning horizon: a) Bio-hub $i=1$ and b) Bio-hub $i=2$

6.4.2.2. Transportation Decisions

In this study, a heterogeneous multimodal transportation network is developed to coordinate biomass logistics between suppliers, bio-hubs, and remote communities. Following the implementation of the replenishment policy, the number of deployed vehicles and vessels at each hub, denoted by z_{ic} , is determined. Specifically, the system incorporates four truck categories with nominal capacities of $c_1=10$, $c_2=30$, $c_3=50$ and $c_4=100$ as well as three ship types with capacities of $c_5=17$, $c_6=30$ and $c_7=50$, each with different cost profiles. These represent a heterogeneous fleet composition designed to balance cost, flexibility, and transport efficiency across diverse demand profiles and route conditions. As presented in Figure 6.8, the first hub primarily deploys medium-capacity trucks (c_2) and large-capacity ships (c_6 and c_7), reflecting its role as the main distribution hub for high-demand communities. The second one relies more on small-capacity trucks (c_1) and medium-capacity ships (c_6 and c_7) as supporter hub.

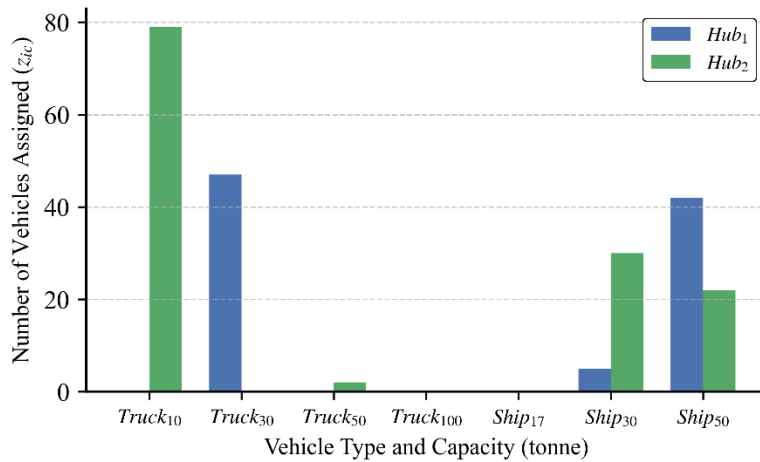


Figure 6.8. Fleet allocation across bio-hubs

Trucks conducted 881 trips throughout the simulation, reflecting their role in frequent, short-haul replenishment between suppliers and hubs. In contrast, ships completed 455 trips, emphasizing their deployment for long-haul deliveries between hubs and remote communities during the May-October navigation window. The total truck rental cost reached \$325,747.19 compared to \$1,914,410.43 for ships which illustrate the significant difference in operational expenditure scale between inland and maritime transport modes. Similarly, CO₂ emissions from truck operations totaled 918,062.921 kg CO₂ eq., while ship emissions amounted to 358,750.108 kg CO₂ eq. This configuration highlights a strategic differentiation in fleet deployment between the two hubs, where proximity, demand intensity, and transport mode selection jointly influence vehicle allocation decisions. The optimized values thus reflect the operational equilibrium achieved between transportation cost minimization, fleet utilization efficiency, and demand responsiveness within the seasonal bioenergy supply network.

To understand the how strategic fleet heterogeneity can improve both the economic and environmental dimensions of biomass logistics, a set of fleet scenarios are analyzed (Figure 6.9). The results indicate that scenarios dominated by small-capacity result in substantially higher CO₂ emissions and total costs. This outcome can be attributed to the increased number of trips required to satisfy biomass demand, which consequently elevates cumulative fuel consumption and transportation expenditures. In contrast, scenarios emphasizing large-capacity assets exhibit notable reductions in both CO₂ emissions and total transportation cost. The improvement is primarily driven by economies of scale, as fewer round trips are required to transport equivalent biomass volumes, which consequently enhance fuel efficiency and reduce the overall carbon footprint. Nevertheless, relying exclusively on large-capacity vehicles may constrain operational flexibility, particularly under conditions of variable biomass availability or seasonal access limitations. The findings further suggest that mixed-fleet configurations integrating medium- and high-capacity vehicles achieve the most balanced performance. These combinations exploit the cost efficiency of larger vehicles while retaining the adaptability of smaller units for short-haul or partial-load operations. Such outcomes reinforce the importance of heterogeneous fleet management in the design of BSCs, as it enables decision-makers to balance cost minimization, emission reduction, and service reliability.

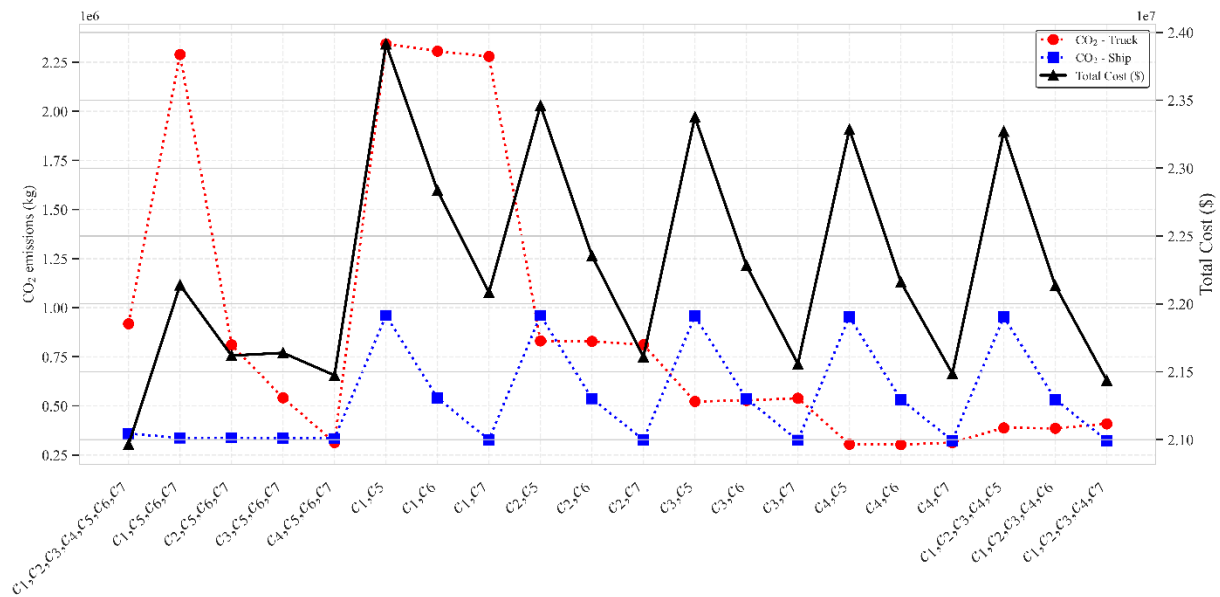


Figure 6.9. CO₂ emissions (truck and ship) and total cost across fleet scenarios

6.4.2.3. Cost profile of the BSC Network

The cost decomposition of bio-hubs and communities within the proposed BSC (Figure 6.10) provides critical insights into the structural determinants of system efficiency and highlights strategic intervention points. At the bio-hub level, transportation dominates the cost structure, with ship operations accounting for approximately 55% of hub-level costs, yet representing only 7.4% of total system expenditures, while truck transportation constitutes 24% of hub costs. This discrepancy highlights that, although ship transportation constitutes the majority of bio-hub level costs due to high per-trip expenditures, its contribution to total system cost is relatively limited because each shipment delivers large volumes that reduce the cost per unit of electricity, reflecting economies of scale. With feedstock procurement and electricity costs each contributing less than 10% of hub-level costs, improvements in these areas would yield marginal savings. Instead, operational efficiencies in transportation logistics, such as route optimization, fleet utilization, and load consolidation, emerge as the most significant lever for reducing hub-level expenditures.

At the community level, inventory management emerges as the predominant cost driver, representing over 50% of community expenditures and more than 40% of total system costs. This concentration highlights the sensitivity of total system cost to inventory policies, where excessive safety stock inflates holding costs and insufficient stock jeopardizes service reliability. Purchasing and electricity costs also represent significant shares, emphasizing the need for

integrated strategies that align procurement, storage, and energy management to maintain operational resilience while minimizing cost.

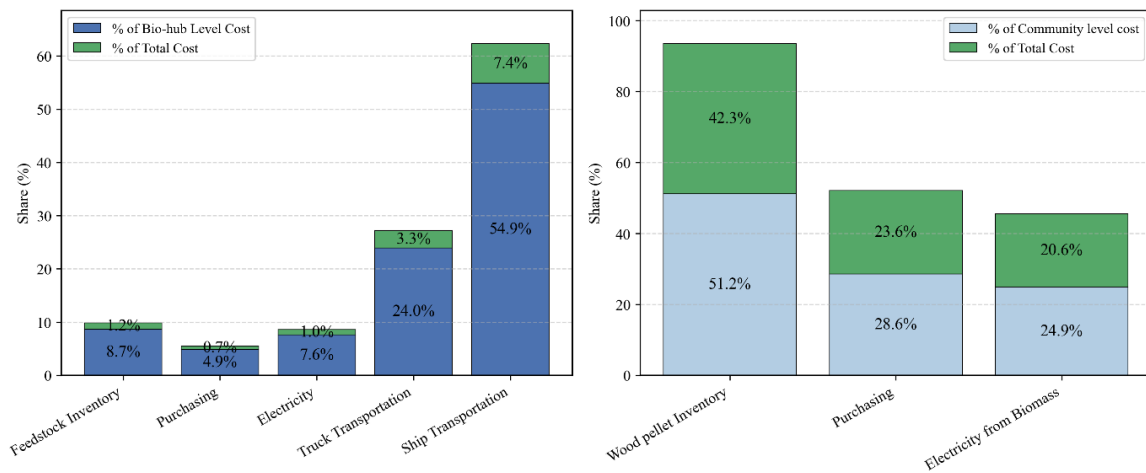


Figure 6.10. Cost profile of BSC entities

6.4.2.4. Capacity Planning of Facilities

Upon solving the decision variables, the storage capacity required for each community, as well as the number of each machine type, could be systematically determined. During the earlier stages of the analysis, the capacity and resource constraints were relaxed to allow the model to identify optimal values of the decision variables necessary to satisfy the projected bioenergy demand. Once these values were obtained, the system's performance was evaluated, and the framework was then used to establish the precise number of resources required to maintain this efficiency under realistic operational constraints. The proposed simulation-optimization framework captures the temporal dynamics of each community throughout the planning horizon, allowing detailed monitoring of inventory behavior, including simultaneous consumption and replenishment. Figure 6.11 illustrates these temporal inventory profiles. The observed time lag between the initiation of inventory accumulation across communities reflects differences in geographical location and logistical accessibility. For instance, the northernmost communities, such as Kangiqsujuaq, Salluit, and Ivujivik, begin receiving shipments later than more accessible communities. In contrast, communities closer to the bio-hubs, such as Kuujjuarapik, commence stocking almost immediately. Building on these temporal inventory patterns, the storage capacity for each community was determined based on the average of the peak inventory levels observed over the planning horizon. Accordingly, the computed capacities for the nine communities are 900, 1500, 450, 3500, 1700, 2000, 750, 620, and 2000 tonnes, respectively. This approach

ensures that each community is equipped with sufficient storage to maintain system efficiency while accounting for logistical constraints and temporal variations in supply and demand.

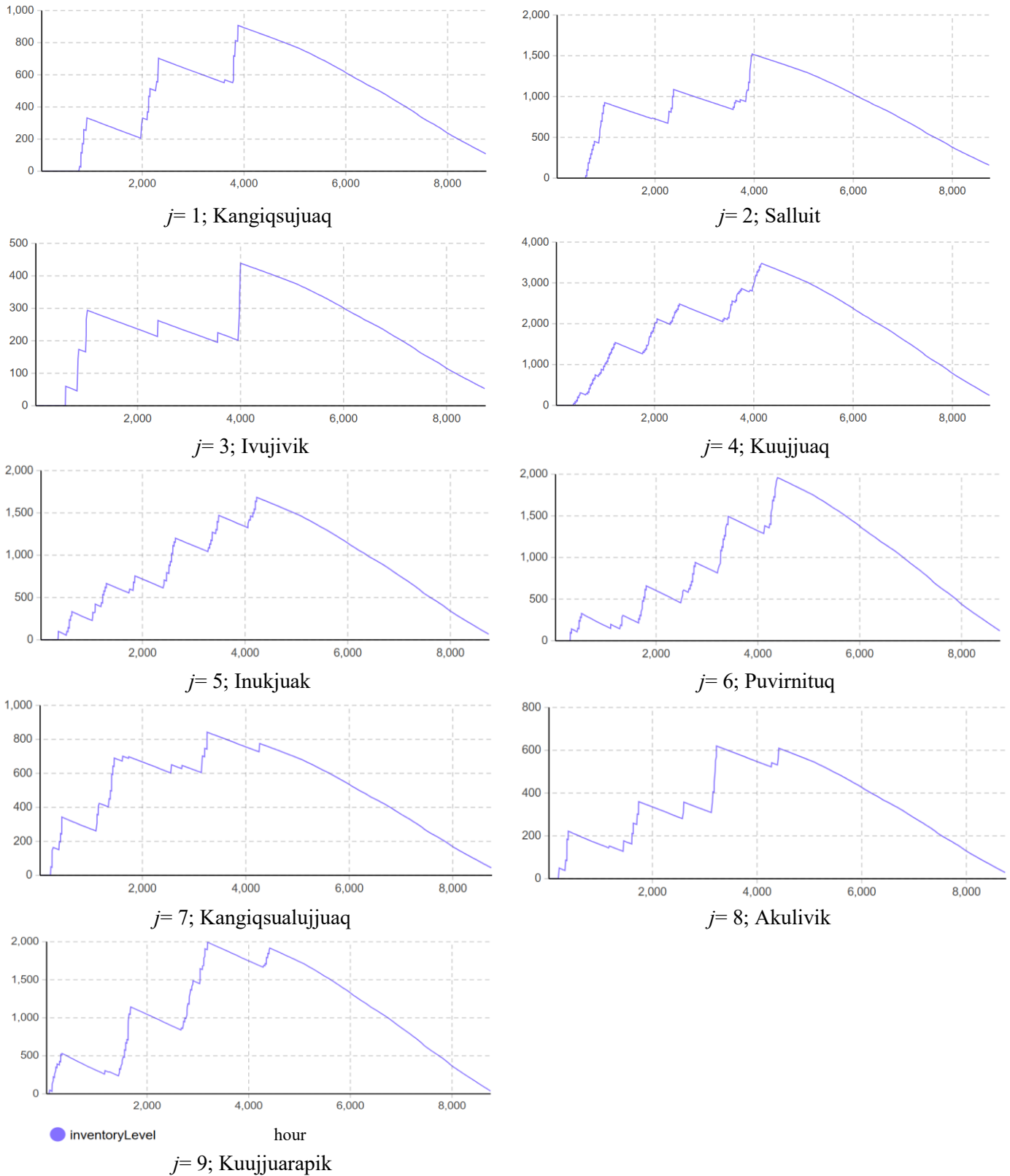


Figure 6.11. Temporal dynamics of inventory levels in remote communities over the planning horizon (x-axis: time in hours; y-axis: inventory level in tonnes).

At the bio-hub level, processing operations rely on four machine types: drum dryer, hammer mill, pellet mill, and cooler. Each machine is defined by its processing capacity, power consumption, and operational reliability parameters, including failure and repair times, which directly affect throughput and system performance. Detailed machine specifications are provided in Table 6.2. Using the simulation framework, the required number of each machine type to meet bioenergy demand was determined, while accounting for potential downtime due to failures and subsequent repair durations. The analysis identified that two drum dryers, six hammer mills, six pellet mills, and seven coolers are necessary to maintain continuous operation under realistic reliability constraints. This configuration maintains operational continuity and energy efficiency despite inherent equipment uncertainties.

To further assess system robustness, an analysis is performed by gradually decreasing the number of each machine type by one unit. The resulting performance variations, illustrated through Figure 6.12, demonstrate the impact of machine reduction on total system cost and bioenergy shortage rates. Specifically, the drum dryer exhibited the highest sensitivity, with a 38.7% increase in shortage and an 11.7% rise in cost when one unit was removed, underscoring its critical role in sustaining process flow and heat demand. In contrast, the hammer mill, pellet mill, and cooler showed comparatively moderate variations, which indicates more flexible capacity margins. These results provide a quantitative depiction of each machine type's relative influence on bio-hub performance and reveal critical dependencies within the processing chain. The heatmap highlights how capacity adjustments can affect production bottlenecks, operational resilience, and overall cost efficiency under stochastic failure conditions.

Table 6.2. Operational characteristics of the machines within bio-hubs

Machine Type	Required number (determined by model)	Capacity (t/h) (input)	Power (kW/h) (input)	Heat Demand (kW/h/t) (input)	Burner Efficiency (%) (input)	Simultaneity Factor (%) (input)	Time Between Failures (h) (input)	Time to Repair (h) (input)
Drum Dryer	2	25	270	1300	50-60	85-100	25	1
Hammer Mill	6	10	370	-	-	85-100	15	0.5
Pellet Mill	6	5	300	-	-	85-100	10	1
Cooler	7	10	25	-	-	85-100	30	0.5

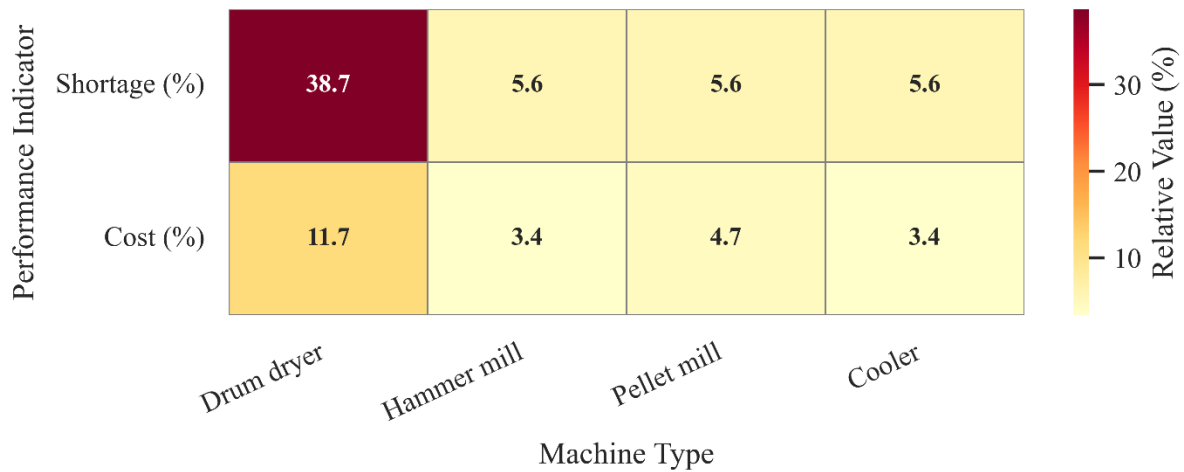


Figure 6.12. Performance comparison of machine types

6.5.2.5. Inventory Frequency

This section highlights the interplay between hub-specific inventory levels and total system cost, demonstrating how replenishment frequency and spatial variability jointly influence operational efficiency and financial performance across the bioenergy network. Figure 6.13 highlights how inventory levels at both hubs adapt to different replenishment intervals (e.g., daily, bi-weekly, and monthly) while also showing the corresponding total system cost. As the review interval increases, both the s and S levels rise substantially, reflecting the bio-hubs' critical role in maintaining higher stock levels in anticipation of community demand. Longer inventory intervals increase the risk of shortages between replenishments; therefore, bio-hubs prefer to hold more inventory on hand to ensure continuous supply, particularly under uncertain delivery and consumption patterns. The first hub exhibits a sharper increase in inventory compared to the second one, indicating their higher demand responsibility which necessitates larger buffers. The total system cost, represented on the secondary y-axis, also rises with longer intervals. This reflects the combined effect of higher procurement and holding costs associated with maintaining larger inventories. The cost increase is particularly marked at the monthly interval, demonstrating the trade-off between service reliability and operational expenditure. Overall, the chart illustrates that bio-hubs strategically scale their inventory in proportion to replenishment frequency. Longer replenishment intervals necessitate higher inventory holdings to mitigate the risk of shortages, while simultaneously increasing system costs as well as electricity unit cost. This highlights the importance of carefully calibrated inventory policies that balance operational reliability with cost efficiency.

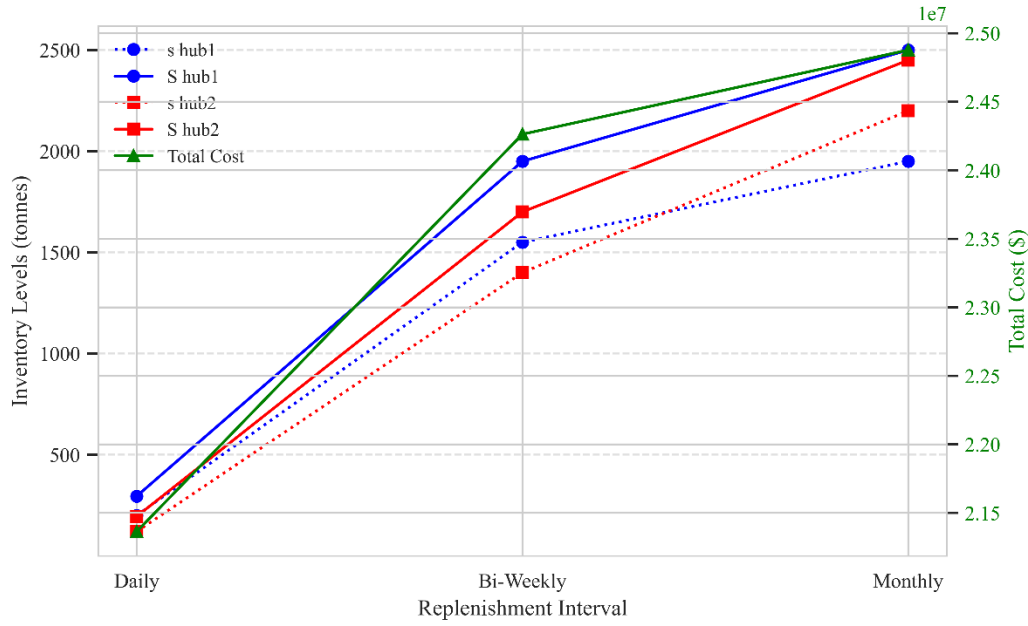


Figure 6.13. Inventory levels for hubs and corresponding total cost within distinct inventory time-intervals

6.5. Conclusions

The conversion of biomass into bioenergy presents a promising pathway for enhancing energy security and promoting the circular economy. However, BSCs are inherently stochastic and vulnerable to supply-demand imbalances and operational disruptions. Considering the critical role of integrated logistics planning in enhancing the resilience and efficiency of BSCs, this study has developed a bi-level DFO framework to systematically coordinate inventory and transportation decisions under uncertainty. To this end, the proposed framework leveraged the strengths of ABS and derivative-free metaheuristics to model a multi-echelon network comprising suppliers, bio-hubs, and power plants, while capturing stochastic dynamics and interdependencies. Given the computational complexity and nonlinearities of the problem, the simulation-optimization approach enabled the identification of near-optimal replenishment policies, transportation schedules, and capacity allocations under operational and disruption risks. The findings suggest that well-coordinated biomass logistics can significantly improve resource utilization, reduce operational costs, and support a sustainable transition toward renewable energy. In the study of remote off-grid communities in northern Quebec, the framework demonstrated that adaptive coordinated planning is critical to maintaining reliable energy supply under extreme conditions. Furthermore, the selection of fleet capacities and scheduling intervals

was found to directly influence service continuity, cost efficiency, and environmental performance.

Future research should build on this bi-level optimization framework by integrating real-time data streams and digital twin architectures to enable adaptive and continuous decision-making under uncertainty. The incorporation of advanced optimization methods, such as metamodel-based approaches, could enhance computational efficiency and responsiveness of the proposed framework. Additionally, adopting blockchain technology would improve data integrity, traceability, and secure information sharing across the SC.

Chapter 7: Conclusion

This dissertation has sought to overcome the limitations of existing modeling and decision-making approaches in the design and management of biomass supply chains (BSCs) under uncertainty. To achieve this, a series of simulation-based and optimization-driven decision-support frameworks (DSFs) were developed, integrating systems modeling, agent-based simulation (ABS), and stochastic optimization techniques. These frameworks were designed to capture the dynamic behavior of BSCs and support resilient, adaptive, and cost-effective operational planning in the presence of disruptions and variability. Their applicability was demonstrated across multiple problem domains, including disruption propagation analysis, adaptive inventory control, and coordinated logistics planning in a bioenergy-based supply chain (SC) network. This chapter summarizes the main findings and contributions of the research presented in the preceding chapters. Additionally, it discusses potential future research directions that can be derived from these findings.

6.1. Summary of Main Findings

Chapter 2 presented a systematic review framework for identifying the key enablers that enhance the large-scale mobilization of bioresources and improve the resilience and adaptability of BSCs. The analysis emphasized the strategic importance of bio-hubs as intermediary nodes that facilitate feedstock aggregation, preprocessing, and logistical coordination. Findings indicated that bio-hub integration significantly enhances the overall efficiency, flexibility, and cost-effectiveness of BSCs by reducing transportation distances, balancing feedstock variability, and improving supply continuity. The results also revealed that existing literature have largely overlooked the operational interdependencies between bio-hubs and other network entities. This underscores the need for integrated modeling approaches that jointly consider strategic design and operational decision-making.

Chapter 3 developed a simulation-based DSF to evaluate disruption propagation and quantify resilience in SCs, specifically BSC networks. The framework captured the dynamic interactions between supply, transportation, and conversion nodes under disruption scenarios. Findings demonstrated that network topology, particularly nodes' criticality and connectivity, substantially influences the performance of the whole system facing unexpected events. The integration of resilience strategies, such as backup suppliers and backup inventories, was shown to significantly reduce disruption impacts and recovery time, with backup inventory emerging as

particularly effective in ensuring continuity of operations under both short-term and prolonged disruptions. The introduction of a dynamic disruption threshold strengthened the framework's ability to adaptively trigger mitigation strategies according to the scale and severity of disruptions. The resilience indicators, quantified through reliability, preparedness, responsiveness, persistence, resourcefulness, and recovery time, offered a comprehensive and multidimensional assessment of network robustness and post-disruption performance, which reflected the multifaceted nature of resilience.

Chapter 4 proposed a simulation-based optimization framework to support inventory planning under stochastic and uncertain conditions. By coupling ABS with an optimization layer, the framework addressed the limitations of traditional optimization models in managing uncertainties (e.g., feedstock quality fluctuations, variable transportation conditions, and preprocessing time) and the interdependence of SC entities. The results highlighted that adaptive order-up-to inventory policies combined with dynamic dual-sourcing mechanisms can maintain system continuity. The hybrid simulation-optimization approach demonstrated superior performance in capturing the stochastic dynamics of BSCs entities, while promoting sustainable and cost-effective bioenergy deployment in remote and off-grid communities. The findings indicated that integrating biomass into the energy network can reduce electricity unit costs and cut CO₂ emissions compared to a diesel-only scenario.

Chapter 5 introduced a bi-level optimization framework for coordinated logistics planning in a fully biomass-dependent energy system. The upper-level model optimized replenishment and capacity allocation under uncertain feedstock availability and conversion performance, while the lower-level model determined optimal transportation planning by considering multimodal routing, heterogeneous fleet configurations, and seasonal accessibility constraints. The iterative coordination mechanism ensured information synchronization between the two decision layers, aligning strategic and operational objectives. Results revealed that integrated replenishment policies improved system efficiency and reduced unmet bioenergy demand. Furthermore, the framework demonstrated that bio-hub-centric coordination enables better resource utilization and stable energy flow continuity, even under severe seasonal and stochastic conditions.

6.2. Research Contributions

The study has bridged several research gaps in the existing literature and made significant contributions in the following areas:

- i. Incorporating bio-hubs as central coordination echelons in BSC design, where feedstock conversion is jointly optimized with production, inventory, and transportation decisions to achieve network-wide coordination across suppliers and biorefineries.
- ii. Operationalizing BSC resilience at bio-hub level by jointly quantifying absorptive, adaptive, and restorative capacities, to provide a multidimensional understanding of system robustness and recovery performance.
- iii. Modeling ripple effects of disruptions originating at or propagating through bio-hubs to assess how localized disturbances propagate through interdependent processes and influence network performance over time.
- iv. Developing derivative-free stochastic simulation-based optimization frameworks centered on bio-hub decision coordination. These frameworks capture the stochastic dynamics, nonlinear interactions, and feedback-driven interdependencies of complex BSC networks without relying on gradient information.
- v. Designing bio-hub-mediated information-sharing mechanisms to improve visibility, facilitate decentralized decision synchronization, and optimize resource allocation across interconnected echelons of the BSC network.

By addressing these challenges and introducing these novel methodologies, this dissertation has advanced the modeling, analysis, and optimization of BSCs under stochastic and disruptive conditions. The proposed frameworks deliver robust and adaptive DSFs that enhance operational efficiency, supply continuity, and resilience while enabling sustainable bioenergy production.

6.3. Future Work Recommendations

The findings presented across this thesis open multiple avenues for advancing the modeling, optimization, and resilience of BSCs. The potential directions for future research can be categorized according to each chapter's methodological focus and analytical contribution. These recommendations emphasize expanding methodological rigor, deepening the integration of uncertainty and resilience, and enhancing the real-world applicability of the proposed framework through digitalization and data-driven approaches.

In the resilience measurement framework (Chapter 4), disruptions were modeled using a predefined set of scenarios representing failures in supplier nodes under varying intensity and duration parameters. To achieve a more realistic representation of network vulnerability, it is recommended that future research incorporate link or connection disruptions (e.g., transportation route failures or communication breakdowns) and examine their influence on the overall resilience of SC networks. Moreover, node disruptions in other critical facilities, such as processing plants, or bio-refineries, can be jointly analyzed with supplier disruptions to provide a more comprehensive understanding of cascading failures and recovery interdependencies. Depending on the nature of the disruption and the underlying network topology, additional resilience strategies such as rerouting, dynamic reallocation of resources, and temporary capacity sharing should be explored to evaluate their effectiveness in maintaining network functionality. Although this chapter presented a comprehensive framework to quantify resilience based on the triple resilience capacities, decision-makers may find it challenging to simultaneously interpret multiple resilience indicators. Therefore, future research is encouraged to employ multi-criteria decision-making techniques to aggregate these indicators into a unified numerical index.

The proposed simulation-based optimization framework for inventory planning in Chapter 5 offers a robust foundation by integrating ABS with an optimization layer and capturing stochastic variations and dynamic interactions in BSCs. While the framework currently supports cost-focused decision-making under uncertainty, extending it to a multi-objective setting would enable simultaneous optimization of economic, service-level, and environmental criteria. The proposed modelling framework represented variability in supply, processing, and transportation operations. However, incorporating additional stochastic drivers, including climate variability, feedstock degradation, and intermodal delays, would further enhance the model realism. Similarly, the current assumption of known demand could be improved by integrating machine learning-based seasonal demand forecasts to better capture real-world fluctuations. The framework's treatment of diesel logistics provides valuable insights into hybrid energy systems, but more detailed modeling of diesel transportation and associated CO₂ emissions could support robust decarbonization analysis. Finally, while the model focused on a single biomass feedstock and conversion process, expanding to multiple feedstocks and alternative conversion technologies such as torrefaction would increase operational flexibility and allow comparative assessment of technological pathways under diverse conditions.

In the bi-level optimization framework for coordinated logistics planning (Chapter 6), a fully biomass-dependent energy system was examined under an information-sharing mechanism, while accounting for supply disruption scenarios and multimodal routing constraints. This

framework provided a robust foundation for analyzing complex BSCs operations by capturing the interplay between strategic and operational decisions, dynamic disruptions, and transportation flexibility. Leveraging these strengths, integrating real-time data streams and digital twin architectures could further enhance the model's capacity for continuous monitoring and dynamic adjustment of operational decisions, enabling more responsive and adaptive management in real-world environments. Building on this foundation, future research could explore adaptive optimization methods, such as reinforcement learning or surrogate-based approaches, to improve computational efficiency and support real-time responsiveness under stochastic conditions. Additionally, the adoption of digital technologies that enhance information visibility, such as blockchain, could improve real-time traceability and data integrity. By enabling secure and transparent information sharing across the network, these technologies can support more effective inventory management, disruption mitigation, and operational decision-making throughout the BSC network. Future studies are also recommended to incorporate first-tier suppliers, such as forestries, along with their transportation networks, and provide a more detailed representation of upstream logistical challenges. By leveraging the framework's multimodal transportation modeling capabilities, variability in harvesting schedules, seasonal accessibility constraints, and vehicle load limitations can be incorporated into system analysis. Accounting for these upstream complexities would enable a more realistic and comprehensive assessment of BSC operations, supporting improved resource allocation, replenishment planning, and operational decision-making across the supply network.

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Appendix A

Table A1. Summary of mathematical programming applications in bio-hub implementation problems

Authors (year)	Bio-Hub Term	Problem	Sustainability Pillar	Modeling Approach	Solution Method	Uncertainty factor	Case Study	Feedstock Type	Final Bioproduct Type
Zhang et al. (2014)	Hub	Lo & BF	Eco	Mathematical programming	Solver		USA	Woody biomass	Commodity chemicals
Marufuzzaman et al. (2014)	Hub	Lo & BF	Eco	Mathematical programming	Accelerated benders decomposition algorithm	Site dependent disruptions	USA		Bioethanol
Xie et al. (2014)	Hub	Lo & BF	Eco	Mathematical programming	Solver		USA	Corn stover & forest residues	Bioethanol
Akhtari et al. (2014)	Terminal	BF & IP	Eco	Mathematical programming	Solver		Canada	Logging residues & sawmill wastes	Heat
Roni et al. (2014)	Depot	Lo & BF	Eco	Mathematical programming	Benders decomposition algorithm		USA	Cellulosic biomass	Biofuel
Lautala et al. (2015)	Depot	Lo	Eco	Mathematical programming (Software-based)	Solver		USA	Woody biomass	Biofuel
Poudel et al. (2016)	Depot	Lo & BF	Eco	Mathematical programming & spatial statistics model	Benders decomposition algorithm	Failure probability associated with link	USA	Corn stover & forest residues	Biofuel
Marufuzzaman et al. (2016)	Terminal	Lo, CP & BF	Eco	Mathematical programming	Solver		USA	Forest residues	Syngas
How et al. (2016)	Hub	Lo & BF	Eco	Mathematical programming & P-graph	Decomposition algorithm		Malaysia	Agricultural residues	
Zhang et al. (2016)	Yard	Lo, CP & BF	Eco	Mathematical programming	Solver		USA	Woody biomass	Bioethanol
Chugh et al. (2016)	Hub	Lo, PP & BF	Eco	Mathematical programming	Solver		USA	Switchgrass	Bioenergy
Lin et al. (2016)	Hub	Lo & BF	Eco	Mathematical programming	Solver		USA	Agricultural residues	Bioethanol
Li et al. (2017)	Pre-treatment facility	Lo & BF	Eco	Mathematical programming &	Solver		USA	Woody biomass	Biofuel
Ng & Maravelias (2017a)	Depot	Lo, CP, TS & BF	Eco	Mathematical programming	Solver		USA	Agricultural residues	Bioethanol

Eco: Economic, **Env:** Environmental, **Soc:** Social, **Lo:** Location, **BF:** Biomass Flow, **CP:** Capacity Planning, **RM:** Resource Management, **VRP:** Vehicle Routing Problem, and **PP:** Production Planning.

Table A1 (Continued)

Authors (year)	Bio-Hub Term	Problem	Sustainability Pillar	Modeling Approach	Solution Method	Uncertainty factor	Case Study	Feedstock Type	Final Bioproduct Type
Maheshwari et al. (2017)	Depot	Lo, CP & BF	Eco	Mathematical programming	Solver based on scenarios	Supply disruption	USA	Corn stover, switchgrass, & miscanthus	
Ng & Maravelias (2017b)	Depot	Lo	Eco	Mathematical programming	Solver		USA	Agricultural residues	Bioethanol
Babazadeh et al. (2017)	Pre-treatment center	Lo & BF	Eco	Mathematical programming & data envelopment analysis	Solver		Iran	Jatropha curcas L. & waste cooking oil	Biodiesel
Zamar et al. (2017)	Depot	BF & VRP	Eco	Mathematical programming	Quantile-based scenario analysis	Feedstock quality, loading, unloading, & transportation time	Canada	Sawmill residues	
Roni et al. (2017)	Depot	Lo & BF	Eco, Env, & Soc	Mathematical programming	Augmented ϵ -constraint		USA	Cellulosic biomass	Bioethanol
Méndez-Vázquez et al. (2017)	Hub	Lo & BF	Eco & Env	Mathematical programming	Solver		Mexico	Agricultural residues	Solid biofuel (pellet)
Gautam et al. (2017)	Terminal	Lo & BF	Eco	Mathematical programming	Solver		Canada	Woody biomass	
Quddus et al. (2017)	Depot	Lo, CP & BF	Eco & Env	Two-stage stochastic modeling	Sample average approximation & progressive hedging algorithm	Supply	USA	Pellet	
Abasian et al. (2017)	Terminal	Lo & BF	Eco	Mathematical programming	Solver		Canada	Woody biomass	
Liu et al. (2017)	Collection center	Lo & BF	Eco	Mathematical programming	Solver	Disruption in collection center & feedstock seasonality	China	Wheat straw	Biofuel
Shamsi et al. (2018)	Collection center	Lo, CP & BF	Eco	Mathematical programming	Solver		Iran	Wheat straw	Bioethanol
Ng et al. (2018)	Depot	Lo, CP & BF	Eco	Mathematical Programming & GIS	Solver		USA	Corn stover	Bioethanol
Malladi et al. (2018)	Yard	BF & VRP	Eco	Mathematical programming	Decomposition-based approach		Canada	Woody biomass	
Dafnomilis et al. (2018)	Terminal	RM	Eco	Mathematical programming	Solver		Netherlands	Wood pellet	

Table A1 (Continued)

Authors (year)	Bio-Hub Term	Problem	Sustainability Pillar	Modeling Approach	Solution Method	Uncertainty factor	Case Study	Feedstock Type	Final Bioproduct Type
Sarker et al. (2018)	Hub	Lo & BF	Eco	Mathematical programming	Branch & bound			Crops, grass & wood residue, & livestock waste	Biomethane gas
He-Lambert et al. (2018)	Preprocessing center	Lo & BF	Eco	Mathematical programming & GIS	Solver		USA	Switchgrass	Biofuel
Aranguren et al. (2018)	Depot	Lo & BF	Eco	Mathematical programming & ALMANAC simulation	Solver		USA	Switchgrass	Biomass co-firing
Asadi et al. (2018)	Distribution facility	Lo, BF & VRP	Eco & Env	Mathematical programming	Genetic algorithm & multi-objective particle swarm optimization	Demand	Iran	Algae	Biofuel
Roni et al. (2019)	Depot	Lo, CP & BF	Eco	Mathematical programming	Solver	Feedstock quality	USA	Agricultural residue, energy crops & municipal solid waste	Bioethanol
Sarker et al. (2019)	Hub	Lo, BF & VRP	Eco	Mathematical programming	Genetic algorithm			Crops, grass & wood residue, & livestock waste	Biomethane gas
Abasian et al. (2019)	Terminal	Lo & BF	Eco	Two-stage stochastic modeling	Multicut L-shaped decomposition algorithm	Demand & final product price	Canada	Woody biomass	
Soren & Shastri (2019)	RBDP	Lo, CP & BF	Eco	Mathematical programming	Solver based on the scenario	Supply disruption		Agricultural residues	
Saadati & Hosseini-zhad (2019)	Hub	Lo, CP & BF	Eco	Mathematical programming	ϵ -constraint		Iran	Bagasse	Bioethanol
Poudel et al. (2019)	Hub	Lo, CP & BF	Eco	Two-stage stochastic modeling	Nested decomposition algorithm, rolling horizon algorithm & variable fixing technique	Feedstock quantity	USA	Corn stover & woody biomass	Biofuel
Aguayo et al. (2019)	Storage facility	Lo & BF	Eco	Mathematical programming	Branch-and-price-based method		USA	Switchgrass	Bioethanol

Table A1 (Continued)

Authors (year)	Bio-Hub Term	Problem	Sustainability Pillar	Modeling Approach	Solution Method	Uncertainty factor	Case Study	Feedstock Type	Final Bioproduct Type
Berg & Athanassiadis (2020a)	Terminal	Lo & BF	Eco	Mathematical programming	Solver		Sweden	Round wood & logging residues	
Aboytes-ojeda et al. (2020)	Hub	Lo & BF	Eco	Two-stage stochastic modeling	Simulated annealing & Tabu search	Feedstock quality	USA		Bioethanol
Guo et al. (2020)	IBLC	PP & RM	Eco	Mathematical programming	Solver		Spain	Wheat straw & wood chips	Fuel pellet
Goettisch et al. (2020)	Depot	Lo & BF	Eco	Two-stage stochastic modeling & ML	Solver	Feedstock quality	USA	Switchgrass	Biomass co-firing
Agar et al. (2020)	Terminal	BF	Eco	Mathematical programming	Solver		Sweden	Woody biomass	
Aranguren et al. (2021)	Depot	Lo & BF	Eco	Two-stage stochastic modeling & ALMANAC simulation	Solver	Feedstock quality	USA	Switchgrass	Biomass co-firing
Nur et al. (2021)	Depot	Lo, CP & BF	Eco	Two-stage Stochastic modeling	Sample average approximation & progressive hedging algorithm	Feedstock quality	USA	Corn stover & switchgrass	Bioethanol
Hossain et al. (2021)	Depot	Lo & BF	Eco	Mathematical programming	Solver		USA	Corn stover & switchgrass	Cellulosic biofuel
Mafakheri et al. (2021)	Hub	BF	Eco	Mathematical programming	Solver		Canada	Wood pellet	Electricity
Mao et al. (2021)	Storage facility	Lo & BF	Eco & Env	Mathematical programming	Genetic algorithm		China	Wheat straw	
Cao et al. (2021)	Collection center	Lo, BF & VRP	Eco	Mathematical programming	Neighbourhood search & tabu search				
Rahimi et al. (2021)	Collection center	Lo, CP & BF	Eco	Mathematical programming	Solver		Iran	Animal waste	Electricity
Aranguren & Castillo-Villar (2022)	Depot	Lo & BF	Eco & Env	Two-stage Stochastic modeling	ϵ -constraint method, particle swarm optimization & simulated annealing	Feedstock quantity	USA	Switchgrass	Biomass co-firing

Table A1 (Continued)

Authors (year)	Bio-Hub Term	Problem	Sustainability Pillar	Modeling Approach	Solution Method	Uncertainty factor	Case Study	Feedstock Type	Final Bioproduct Type
Aboytes-Ojeda et al. (2022b)	Depot	Lo & BF	Eco	Two-stage Stochastic modeling	L-shaped with connectivity constraints	Feedstock quality	USA	Switchgrass	Bioethanol
Zarei et al. (2022)	Storage facility	Lo & BF	Eco	Multistage risk-based stochastic model	Solver	Feedstock quantity & demand	South Korea,	Pellets, wood chips & seaweed	Biofuel
Abusaq et al. (2022)	Depot	Lo, CP & BF	Eco & Env	Mathematical programming	Fuzzy flexible robust possibilistic programming	Feedstock quantity & demand	Pakistan	Agricultural residue	Bioenergy
Gautam et al. (2022)	Terminal	Lo & BF	Eco & Soc	Mathematical programming, MCDM & benefit-cost analysis	Solver		Canada	Woody biomass	Heat & electricity
Geismar et al. (2022)	Depot	Lo, CP & BF	Eco	Stochastic modeling	Decomposition algorithm	Feedstock quantity	USA	Lignocellulosic biomass	Bioethanol
Abbasi et al. (2022)	Collection center	Lo, BF & VRP	Eco & Env	Mathematical programming	Solver & Genetic algorithm		Iran	Municipal solid waste	Electricity
Lam et al. (2023)	Hub	Lo, BF & TS	Eco	Mathematical modeling & P-graph	Solver		Malaysia	Agricultural residues	
Li et al. (2023)	Depot	Lo, BF & VRP	Eco & Env	Mathematical programming	Genetic & ant colony algorithms				
Pandey et al. (2023)	Preprocessing facility	Lo, CP & BF	Eco & Env	Mathematical programming	Solver	Feedstock quantity	USA	Corn stover	Bioethanol
Li et al. (2024)	Depot	Lo & BF	Eco	Mathematical programming	Solver		USA	Forest residues	Biofuel
Hossain et al. (2024)	Depot	Lo, BF, CP & VRP	Eco	Mathematical programming	Solver		USA	Miscanthus, switchgrass & corn stover	Biofuel
Singh et al. (2024)	Depot	Lo, BF& CP	Eco, Env, & Soc	Mathematical programming	Augmented ϵ -constraint & lexicographic technique			Waste animal fat	Biodiesel

Table A2. Summary of simulation and MCDM applications in bio-hub implementation problems

Authors (year)	Bio-Hub Term	Problem	Sustainability Pillar	Modeling Approach	Aim	Case Study	Feedstock Type	Final Bioproduct Type
Wolfsmayr et al. (2016)	Terminal	Lo, BF & RM	Eco	DES	Investigating the efficiency of adopting the existing railway sidings to provide multimodal terminals	Austria	Woody biomass	Biofuel
Väättäinen et al. (2017)	Terminal	Lo, BF & RM	Eco	DES	Evaluating the performance of the BSC with intermediate terminals at different distances.	Finland	Forest chip	Heat & power
Fernandez-Lacruz et al. (2019)	Terminal	BF & RM	Eco	DES	Evaluating the efficiency of terminals in supplying biomass to CHP and biorefineries with varying sizes	Sweden	Woody biomass	Heat & power
Enström et al. (2021)	Terminal	BF & RM	Eco	DES	Evaluating the performance of the BSC with intermediate terminals at different distances.	Sweden	Wood chips	Biofuel
Khoddami et al. (2021)	Hub	BF	Eco	System dynamics	Comparing coordination strategies of quantity discount and cost-sharing to coordinate the BSC with hubs	Canada	Wood pellet	Electricity
Kühmaier et al. (2014)	Terminal	Lo	Eco & Env	AHP & fuzzy set theory	Determining the most suitable areas for energy wood storage terminals	Austria	Woody biomass	
How & Lam (2017)	Hub	Lo	Eco	AHP & PCA	Determining the most suitable areas for hubs	Malaysia	Agricultural residues	
Lemire et al. (2019)	Depot	Lo, CP & BF	Eco	AHP, GIS & software-based optimizer	Determines the suitable locations, allocations, sizing, and number of depots according to different demand location scenarios.	Canada	Corn stover	Cellulosic sugar
Muerza et al. (2023)	IBLC	SS & PP	Eco, Env & Soc	AHP, TOPSIS, DES & agent-based simulation	Evaluating the economic and environmental feasibility of implementing IBLCs with a focus on purchase problem of agricultural residues	Spain	Wheat straw residuals & wood chips	Wood pellet

Eco: Economic, **Env:** Environmental, **Soc:** Social, **Lo:** Location, **BF:** Biomass Flow, **CP:** Capacity Planning, **PP:** Production Planning, **RM:** Resource Management, and **SS:** Supplier Selection.

Table A3. Summary of systematic modeling applications in bio-hub implementation problems

Authors (year)	Bio-Hub Term	Problem	Sustainability Pillar	Modeling Approach	Aim	Case Study	Feedstock Type	Final Bioproduct Type
Muth et al. (2014)	Depot	PE	Eco & Env	TEA	Analyzing the effects of distributed preprocessing supply system and conventional supply system designs in terms of cost and environmental sustainability	USA	Woody biomass	Bioethanol
Lamers et al. (2015a)	Depot	TS	Eco	TEA	Analyzing different depot configurations to compare the possibility of adopting sophisticated pre-treatment technologies	USA	Corn stover & woody biomass	Bioethanol
Liu & Bao (2019)	Regional biomass collection depot	TS	Eco	TEA	Evaluating the efficiency of adopting dry acid pre-treatment technology in depots	China	Agricultural residues	Bioethanol
Patel et al. (2019)	Mobile pyrolysis system	TS	Eco	TEA	Evaluating the technical and financial viability of switching from centralized to decentralized pyrolysis units	Canada	Woody biomass	Bio diesel
Lan et al. (2021)	Depot	Lo & TS	Eco	TEA	Evaluating several supply chain configurations with various biomass blending ratios and different biorefinery and preprocessing sites, as well as alternative preprocessing technologies.	USA	Forest residues & switchgrass	Gasoline & bio diesel
Dias (2014)	Terminal	PE	Env	LCA	Evaluating the environmental impact of roadside chipping of loose residues, terminal chipping of loose residues, and terminal chipping of bundled residues	Portugal	Eucalypt logging residues	Fuel chips
Nguyen et al. (2014)	Depot	Lo & CP	Env	LCA	Evaluating the impact of location and size of preprocessing depots in GHG emissions from agricultural residue logistics.	USA	Corn stover	Bioethanol
de la Fuente et al. (2018)	Terminal	PE	Env	LCA	Evaluating environmental profiles of woody pellets production from logging residues in terminal-based and land-based scenarios	Sweden	Woody biomass	Wood pellet
Kim et al. (2019)	Depot	PE	Eco & Env	LCA	Evaluating the environmental impacts of integrating a decentralized (depot-based) biorefinery with a coal-fired power plant.	USA	Corn stover	Biomethane
Lan et al. (2020)	Depot	PE	Env	LCA	Evaluating the life-cycle primary energy consumption and global warming potential of alternative biorefinery systems with and without a decentralized depot	USA	Pine residue & switchgrass	Gasoline & bio diesel

Eco: Economic, **Env:** Environmental, **Lo:** Location, **CP:** Capacity Planning, **TS:** Technology Selection, and **PE:** Performance Evaluation.

Table A3 (Continued)

Authors (year)	Bio-Hub Term	Problem	Sustainability Pillar	Modeling Approach	Aim	Case Study	Feedstock Type	Final Bioproduct Type
Toba et al. (2023)	Depot	Lo	Eco & Env	Graph Theory & K-means clustering	Determine the most suitable areas for depots	USA	Agricultural residues & energy crops	Bioenergy
Lamers et al. (2015b)	Depot	PE	Eco	Financial analysis	Calculating and comparing the total cost of the conventional supply system and advanced supply system with depot	USA	Corn stover & woody biomass	Bioethanol
Virkkunen et al. (2016)	Terminal	PE	Eco	Financial analysis	Analyzing terminal cost for forest fuel supply	Finland	Woody biomass	Biofuel
Berg & Athanassiadis (2020b)	Terminal	PE	Eco	Financial analysis	Evaluating the procurement cost of biomass supply to a potential biorefinery with different terminal configurations	Sweden	Forest residues	
Martinkus et al. (2018)	Depot	Lo	Eco	Financial analysis coupled with decision matrix	Determining the most suitable areas for depots	USA	Agricultural residues	Biofuel
Han et al. (2021)	Depot	PE	Eco	Financial analysis	Evaluating year-round storage operation of three agricultural residues under dry acid pre- treatment method at regional collection depots	China	Agricultural residues	
Kim et al. (2018)	Depot	PE	Eco & Env	Descriptive statistics	Evaluating the efficiency of a depot-based decentralized biorefinery system in the energy independence and security act compliant bioethanol production	USA	Agricultural residues	Bioethanol