Designing Incentive Mechanisms for Sustainable Biomass Supply Chain Systems: An Application of the Pulp and Paper Sector

by

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Abstract

This thesis examines the design of incentive mechanisms for sustainable biomass supply chain systems focusing on the pulp and paper sector. The study utilizes a combination of literature review, quantitative modeling, and numerical analysis to identify an appropriate subsidy program for the local government to ensure the truth-telling of pulp and paper mills under the cap-and-trade mechanism using the Lagrange model. The analysis shows that the government helps low-demand and high-demand mills, but the help for the high-demand mill leads to more sustainable decisions, while the support for the low-demand mill keeps an economic disaster from happening. The thesis also proposes specific recommendations for the design of cap-and-trade mechanisms in the pulp and paper sector. The local government's decision to raise the price of carbon under a favorable subsidy contract that considers the views of all members would be environmentally beneficial. Overall, the thesis contributes to understanding how incentivizing mechanisms promote sustainability in biomass supply chain systems with asymmetric information.

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List of Abbreviations and Terms

This glossary briefly overviews abbreviations and terms used within this dissertation.

Abbreviation	Meaning
AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
BWM	Best-Worst Method
CVaR	Conditional Value at Risk
CSR	Corporate Social Responsibility
DEA	Data Envelopment Analysis
DEMATEL	Decision-making Trial and Evaluation Laboratory
DSS	Decision Support System
Electre	Elimination Et Choix Traduisant la REalité
GHG	Greenhouse Gas
SBSC	Sustainable Biomass Supply Chain
SWOT	Strengths, Weaknesses, Opportunities, and Threats
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TPL	Triple Bottom Line
VIKOR	VIseKriterijumska Optimizacija I Kompromisno Resenje

Chapter 1. Introduction

Due to its wide availability, biomass has been a popular source of bioenergy feedstock in recent years. Biomass feedstock sources include forest-based residues, agricultural residues, energy crops, biodegradable substances of finished products, and industrial and municipal solid wastes utilized to produce bioenergy and bioproducts (Ghaderi et al., 2016). According to a recent report published by the International Renewable Energy Agency (IRENA), biomass consumption share was 10% of the global energy source in 2010 and is predicted to double by 2030 (Hiloidhari et al., 2017; IRENA, 2015). Nevertheless, the proper supply of biomass feedstock faces numerous challenges that require effective management. Biomass supply chains must cope with the harvesting, collection, storage, and transportation operations of such masses (Sansaniwal et al., 2017). Particular characteristics of this sector include high moisture content, seasonal availability, significant fragmentation, and low bulk density (Sun & Fan, 2020). Biomass supply chain players must also deal with problem-solving scenarios under uncertainty related to weather conditions and market demand fluctuations (Shabani & Sowlati, 2016). In particular, due to the digitalization of paper-based media, low-cost worldwide competition from emerging economies, and excess global supply of their products, the Canadian pulp and paper industry has faced a fall in demand for traditional pulp and paper products over the previous decade (PriceWaterhouseCoopers, 2010). Therefore, implementing effective strategies to address demand concerns in this industry is explored in this thesis.

In recent decades, moving towards sustainable development has mainly addressed the rise of public concerns about climate change issues. Sustainable supply chains focus on incorporating environmental- and social-friendly practices into their operations (Dharmawan et al., 2020). Acknowledging the economic advantages of biomass business operations, the utilization of forest-agri-residues for bioenergy and biofuels generation could lead to environmental and social betterments, including (1) improving the air quality by curbing GHG emissions traditionally discharged from mass burning facilities, (2) decreasing waste mass and saving landfill spaces, (3) diminishing fire risks through the collection of post-thinning residues, (4) creating new job opportunities in less-developed communities, and (5) reducing local and global dependency on fossil-based reserves (Forest-and-Rangelands, 2015). To implement sustainability-driven strategies, supply chain players not only account for environmental and social concerns but also require exploring proper regulatory mechanisms to minimize costs.

To promote business sustainability, efficient local legislation and global strategies have been developed to contribute towards a transition from fossil-fuel consumption to renewable-resource utilization (Sansaniwal et al., 2017). Additionally, biomass supply chains are expected to align their business values and operations with globally-practiced binding regulations, certification programs, and monitoring processes to meet sustainability goals (IRENA, 2021). Therefore, there have been emerging motives to explore optimal decision-making strategies that benefit both SBSC actors and government bodies. Having completed a systematic literature review on SBSC management, I categorize such regulatory mechanisms in Section 2.3.2 and

articulate my proposed model in this thesis to account for incentivizing and controlling frameworks.

The process of producing paper from forest-based biomass feedstocks emits many GHG emissions. Among various preventive, incentivizing, and controlling instruments for GHG emissions reduction, emissions pricing has been widely adopted by governments around the globe, where business enterprises cope with a trade-off between their optimal production plans and emissions expenses. Different emission pricing programs exist, such as carbon tax, carbon cap-and-trade, and carbon offset, to decrease the amount of GHG discharges. Adopting the Canadian Net-Zero Emissions Accountability Act is essential to achieve net-zero GHG emissions by 2050[1]. In the case of the pulp and paper industry, the federal sustainable development plan, enacted in 2010, considers the preservation and sustainability of this heritage to be a critical matter due to its significant socioeconomic impact. Implementing new technologies helps pulp and paper mills lower GHG emissions and enhance energy efficiency (Environment Canada, 2016). Accordingly, the Canadian government has developed incentive programs to support pulp and paper firms and lessen GHG emissions and fossil energy dependence (Natural Resources Canada, 2012). In Canada, Ontario has developed a cap-and-trade policy, while New Brunswick, Nova Scotia, and Prince Edward Island have adopted an offset policy (Pan-Canadian Framework on Clean Growth and Climate Change, 2016).

[1] https://www.canada.ca/en/services/environment/weather/climatechange/climate-plan/net-zero-emissions-2050/canadian-net-zero-emissions-accountability-act.html

Due to the wide availability of forest-based biomass feedstocks in Canada, the pulp and paper sector has formed one of the country's most profitable industries. Accordingly, this study aims to investigate Canada's pulp and paper industry, considering the government's role in promoting sustainability development. In this study, a forest supplier provides the pulp and paper mill's raw materials: pulp logs. I exclude the flows of pulp logs and wood chips to the mill under consideration. My proposed network has two decision-makers: the pulp and paper mill and the government. The latter regulatory body actively accounts for sustainability-conscious operations and strategies. In my model, the local government monitoring the network uses a cap-and-trade mechanism along with subsidy programs to encourage the pulp and paper company to invest in technology improvement toward greener operations. In this cap-and-trade formation, the government sets an upper limit on the amount of GHG the pulp and paper company may emit but allows additional capacities to be purchased from other organizations that have not used their emissions allowance fully. The pulp and paper mill's demand pattern is private information in the proposed model. It is assumed that the entire demand must be met.

Meanwhile, according to the previous estimations, the local government can quantify the probability that the production company's demand level could be categorized as low or high. Note that a more elevated pulp and paper demand results in more carbon emission, which needs more technology improvement investment to reduce the mill's carbon trading costs of the cap-and-trade mechanism. In such a case, the government offers a subsidy program and transfer payment using a principal-agent contract, according to such asymmetric information on the demand level, encouraging the pulp

and paper company to boost its green investments, thus, curbing environmental consequences. A Lagrange model solves the problem and gets decision variables, including investment level and subsides. Figure 1.1 depicts a schematic of the forest-based SBSC of interest and network interactions, while Figure 1.2 shows the sustainable pulp and paper problem studied in this thesis.

The rest of this thesis is as follows: In chapter 2, a systematic literature review of SBSC management, research gaps, and questions are provided. That review covers quantitative papers on SBSC cases between 1987-2020. Chapter 3 includes methodology, model specification, and mathematical modeling centered on game theory. Chapter 4 provides a numerical analysis of the studied model. Last but not least, Chapter 5 addresses the conclusion of the explored SBSC problem.

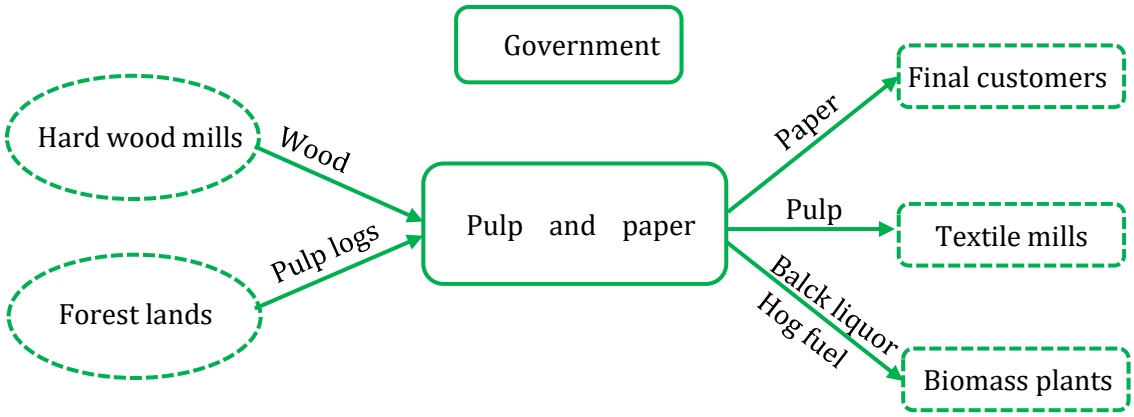

Figure 1.1. A generic forest-based SBSC.

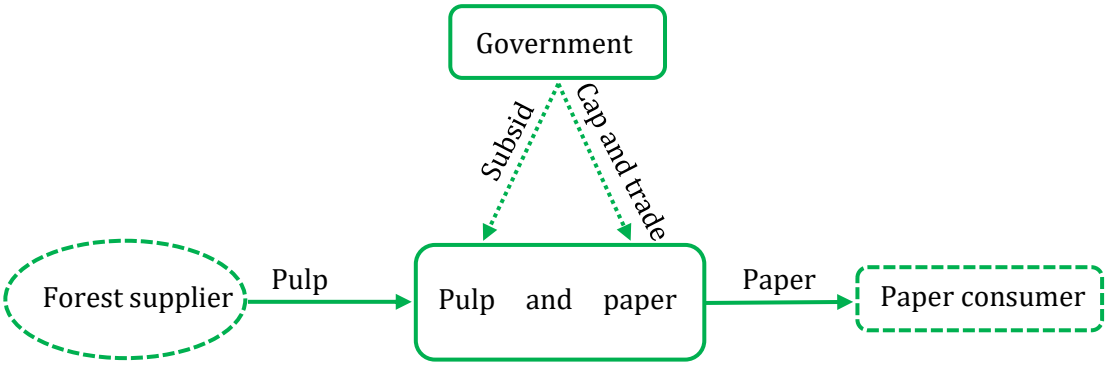

Figure 1.2. The forest-based SBSC under study.

Chapter 2. Literature Review

In this chapter, I provide a systematic literature review on SBSC-oriented models and investigate the role of governments' policies on sustainability development. Although numerous studies incorporate quantitative methods, the existing literature systematically lacks a thorough review of previous studies and characterizing regulatory perspectives. To bridge this gap, my literature review examines prior work published in the SBSC context focusing on the significant role of policymakers who advance the sustainable development of the biomass sector. A two-step search procedure is established in Web-of-Science and Scopus databases to comprehensively collect published materials. I classify the existing literature through a content analysis approach, extracting structural dimensions from inductive and deductive categorization methods. The content analysis review process includes four steps: (1) material selection, (2) descriptive analysis, (3) categorization, and (4) evaluation of the collected materials (Seuring & Gold, 2012). My study's final literature pool comprises 450 published, peer-reviewed academic journal articles in the SBSC context. These papers are shortlisted from my keyword-based search within the period of January 1, 1987, to August 9, 2020, which initially led to 2538 references. Applying deductive and inductive methods, I first identify the structural dimensions and analytic categories and then review the final literature pool according to the classes shown in Figure 2.1.

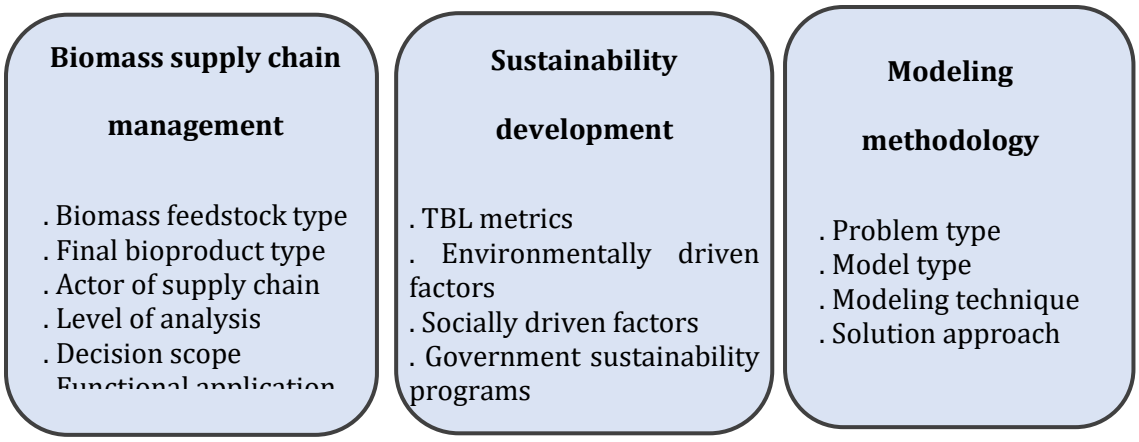

Figure 2.1. The triple research streams addressed in the SBSC management sector.

2.1. Research methodology

In the literature review phase, a systematic literature review approach is applied to provide a rule-governed content analysis (Seuring & Gold, 2012). This methodology employs four sequential levels of analysis, including (1) material collection, (2) descriptive analysis, (3) categorization, and (4) evaluation. In the following subsections, the four-step literature review method is explained.

2.1.1. Material collection

In this section, the material collection process is discussed. I note that a unit of research is defined as a single journal article published in English. The material collection procedure is summarized in Table 2.1. and described in detail as follows:

(1) *Determining appropriate keywords:* My keywords are classified into three research fields: supply chain terminology, sustainability pillars (Elkington, 1997), and biomass. The initial keyword search, which is not restricted to studies that explore quantitative methods, enables me to gather a broader spectrum of papers addressing the SBSC agenda. I develop three sets of keywords by adopting search

recommendations of prior literature review studies. Regarding the first research field, I consider “supply chain”, “supply-chain”, and “logistic” combinations from supply chain-related terminology (Hassini et al., 2012). To explore the sustainability paradigm, I search for the “sustainable”, “sustainability”, “environment*”, “social*”, “ecological”, “green”, “ethic*”, “reverse”, “closed-loop”, and “closed loop” terms (Govindan et al., 2015; Seuring & Müller, 2008). Finally, I examine the biomass context using a diverse selection of “bio*mass”, “bio-mass”, “bio*energy”, “bio-energy”, “bio*fuel”, “bio-fuel”, “bio*ethanol”, “bio-ethanol”, “bio*gas”, “bio-gas”, “bio*oil”, “bio-oil”, “bio*diesel”, “bio-diesel” (Ghaderi et al., 2016). Accordingly, I offer the following Boolean keyword combination: (“supply chain*” OR “supply-chain*” OR “logistic*”) AND (“sustainable” OR “sustainability” OR “environment*” OR “social” OR “green” OR “ ecological*” OR “ethic*” OR “reverse” OR “closed-loop” OR “closed loop”) AND (“bio*mass” OR “bio-mass” OR “bio*energy” OR “bio-energy” OR “bio*fuel” OR “bio-fuel” OR “bio*ethanol” OR “bio-ethanol” OR “bio*gas” OR “bio-gas” OR “bio*oil” OR “bio-oil” OR “bio*diesel” OR “bio-diesel”).

(2) *Conducting the preliminary search:* In the second phase of material collection, I explore the Scopus database using the keywords mentioned above in the “title, abstract, keywords” fields, with a focus on peer-reviewed papers published from January 1, 1987, to August 9, 2020. I choose this timeframe to thoroughly analyze the sustainable development paradigm targeted by the United Nations’ Brundtland Commission (WCED, 1987). This search results in a collection of 1,998 studies on Scopus. I reduce the scope of my analysis by focusing on the following research disciplines: Agriculture, Business, Computer Science, Decision Sciences,

Economics, Energy, Engineering, and Mathematics. The remaining 1,485 publications shape my primary review pool for this study.

(3) *Reviewing, refining, and filtering the literature:* In the third phase of material collection, the titles, keywords, and abstracts of 1,485 short-listed articles are investigated to conduct an inductive filtering process. I identify the set of short-listed technical articles that explore all three aspects that comprise my review study's focus points: supply chain management, sustainability development, and the biomass sector. Additionally, I eliminate conference papers, technical reports, book chapters, literature review studies, and notes found in the 1,485-reference pool. This refining procedure offers a reference pool of 597 studies available on Scopus as of August 9, 2020.

(4) *Enhancing the exclusiveness of the reference pool*: I repeat the three phases explained above using the Web-of-Science (WoS) database and identify the relevant papers not available on Scopus. This phase adds a set of 208 articles to my final list, bringing my material collection size to 805 academic units. Afterward, I re-examine the full texts and concentrate on the studies that apply quantitative techniques (including descriptive, predictive, and prescriptive analytics). This procedure leaves me with a final list of 450 references published between 2003 and 2020 in peer-reviewed English journals and examining quantitative methods in the SBSC context.

Table 2.1. The material collection procedure in the current review study.

	Items	Processes/Criteria	Studies
1	Defining the unit/period of study	Study type: peer-reviewed English journal papers Time period: January 1987 to August 2020	-

	Items	Processes/Criteria	Studies
2	Developing the search keywords	"Supply Chain Management" AND "Sustainability" AND "Biomass"	-
3	Searching on Scopus	Exploring papers on Scopus in the "Title, Abstract, Keywords" fields	1,998
4	Refining the studies according to the subject areas	Filtering the Scopus results based on the targeted subject areas	1,485
5	Refining the studies according to the search fields	Analyzing the keywords, titles, and abstracts of the remaining studies to find those addressing all fields of (1) "supply chain management", (2) "biomass sector", and (3) "sustainability development" and to exclude work that does not cover my review scope	597
7	Searching on WoS	Exploring papers on WoS following the steps mentioned above	208
6	Refining the studies according to the decision-making methodology	Analyzing the full texts of the short-listed publications to explore papers addressing quantitative techniques	450

2.1.2. Descriptive analysis

The current proposal uses a descriptive analysis of the SBSC literature to identify the distribution of the reviewed studies over time and across different journals. Such an analysis helps researchers recognize leading journals and promising research trends. My discussion in Section 2.3 provides detailed findings of my descriptive analysis.

2.1.3. Categorization

Category selection is critical to my content analysis process. Adopting the refining procedure, illustrated in Table 1, and applying both deductive and inductive methods, I classified my study's various analytic categories and structural dimensions into four research areas: supply chain management, biomass sector, sustainability development, and modeling methodology. Before a full-text analysis, a deductive review approach is applied to identify the analytic categories and research classes addressed in the previous review studies (Seuring & Gold, 2012). I then define more analytic categories unique to my review (Seuring & Gold, 2012). Table 2.2 lists the

final categories considered in the current proposal based on deductive and inductive classifications.

Table 2.2. Category selection elements considered in the current study, based on deductive and inductive classification.

Research perspective	**Structural dimension**	**Analytic categories**	**Deductive and inductive coding**
Biomass supply chain management	Feedstock type	Energy crops, forest-based biomass, agricultural residues, agriculture wastes, industrial wastes, microalgae, municipal solid wastes, marine biomass resources	(Cambero & Sowlati, 2014), (Pan et al., 2015), and inductive coding
	Final bioproduct type	Biofuel, bioenergy, electricity (power), heat, bio-chemicals, biomaterial, multiple products	(Shabani et al., 2013), (Ghaderi et al., 2016), and inductive coding
	Actor of supply chain	Supplier, farmer, preprocessor, bio-conversion firm, distributor, retailer, end users, government, bank, recycler	(De Meyer et al., 2012) and inductive coding
	Level of analysis	Microscopic level (Intra-Organizational): Firm Mesoscopic level (Inter-Organizational): Chain, network, dyad Macroscopic level (Sector-Wide Aggregate): Industry, macro-economy	(Rebs et al., 2018)
	Decision level	Strategic, tactical, operational	(De Meyer et al., 2014) and (Ghaderi et al., 2016)
	Functional application	Biomass feedstock supply, supply chain coordination/contracting location, network design, production planning, inventory, transportation, routing, pricing, information	(Brandenburg et al., 2014) and inductive coding
Sustainability	TBL metrics	Economic, environmental, social	(Gabrielle et al., 2014) and (Budzianowski & Postawa, 2016)
	Environmentally-driven practices	GHG emissions, life cycle assessment, indirect environmental benefit, land use, soil quality, water use and efficiency, water resources quality, other emissions, waste reduction, biological diversity, logistical distance to ecological units	(Gabrielle et al., 2014) and (Budzianowski & Postawa, 2016)
	Socially-driven practices	Job creation, safety, social services, food security, poverty reduction, child labor matters, CSR investment, consumer surplus, community improvements	(Gabrielle et al., 2014) and (Budzianowski & Postawa, 2016)

Research perspective	Structural dimension	Analytic categories	Deductive and inductive coding
	Government sustainability regulations	Incentive programs, subsidies, tax policies, government regulation	(Gonzalez-Salazar et al., 2017), (Pashaei et al., 2018), and inductive coding
Modeling Methodology	Type	Deterministic/ uncertain	(Barbosa-póvoa et al., 2018)
	Modeling approach	(1) Mathematical programming: Mixed-integer programming, linear programming, multi-objective programming, stochastic programming, non-linear programming, epsilon constraint, robust optimization, goal programming, P-graph, chance constraint, CVaR, constraint programming	(Soto-Silva et al., 2016) and inductive coding
		(2) Multi-criteria decision-making: AHP/ANP, DEA, DEMATEL, TOPSIS, VIKOR, SWOT, Electre, best worst method	(Brandenburg et al., 2014) and inductive coding
		(3) Simulation modeling: System dynamics, Monte Carlo, discrete event, spreadsheet analysis, agent-based model, business process simulation	(Brandenburg et al., 2014) and inductive coding
		(4) Systematic modeling: Financial analysis, life cycle analysis, structural analysis, descriptive statistics, software-based, techno-economic, DSS, input/output analysis, regression analysis, statistical hypothesis testing	(Brandenburg et al., 2014) and inductive coding

2.1.4. Material assessment and methodological rigor

The next step of a systematic literature review includes comprehensively reviewing the final reference pool's content, where the collected publications are assigned to the analytic categories and structural dimensions discussed above.

2.2. Findings of descriptive analysis

A descriptive analysis of the short-listed papers centered on the research trends and the influential journals in the SBSC context is provided (Seuring & Gold, 2012). Figure 2.2 illustrates the distribution of 450 reviewed publications over time and provides evidence of a growing trend in incorporating sustainability-conscious perspectives

and quantitative analytics in biomass supply chain applications. Although I designed my keyword search for the 1987-2020 timeframe, the first paper meeting my selection criteria was published in 2003. Van Belle et al. (2003) investigate forest residue sources recycled by a wood-fuel supply chain accounting for various economic and environmental constraints.

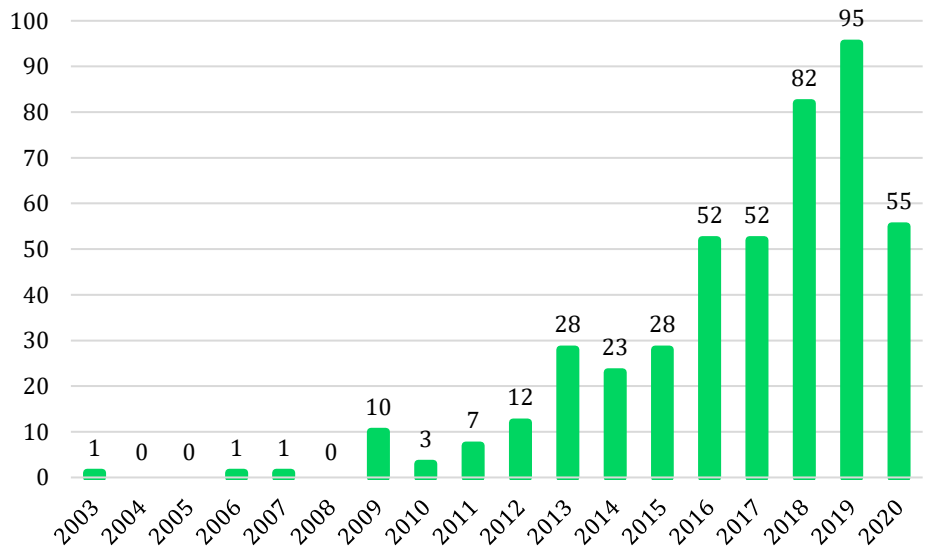

Figure 2.2. Distribution of the publications in the SBSC research area by year.

The leading journals in my SBSC review are listed in Figure 2.3. Overall, the collected papers are published in 99 outlets across various disciplines, where 346 references (77 percent of the reference pool) are published in 24 journals.

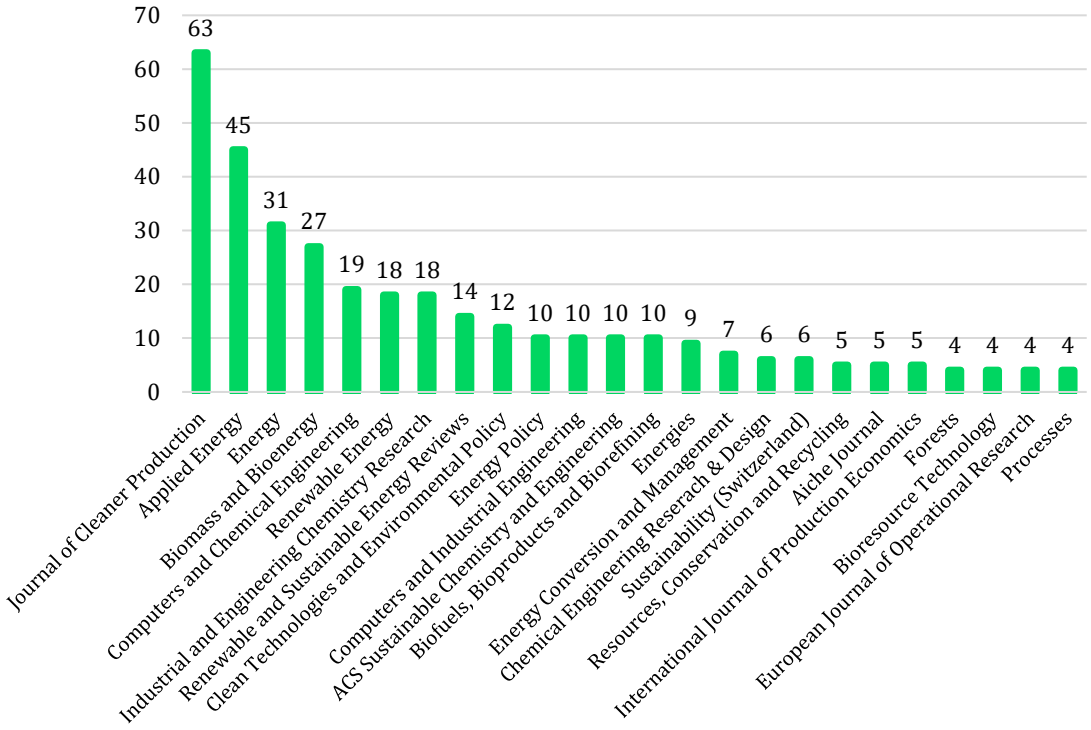

Figure 2.3. Distribution of the publications in the SBSC research area by leading journals.

2.3. Findings of the content analysis

In this section, I present the results of my content analysis on the structural dimensions and related analytic categories identified in Table 2.3.

2.3.1. Biomass supply chain management

In this segment, I review the literature of biomass supply chain management, focusing on four structural dimensions mentioned in Table 2.2: actor of analysis, level of analysis, decision level, and functional application. The biomass supply process initiates from a production facility to a bioconversion plant through a chain of operations. Figure 2.4 demonstrates operational interdependencies across a generic biomass supply chain (De Meyer et al., 2012). Six main entities are in the biomass-to-bioproduct supply chain: biomass production, harvest, collection, pre-treatment,

storage, and bioconversion facility. The operations of biomass supply chains are highly interconnected, so upstream decision-making strategies affect downstream operations in the network (Allen et al., 1998). According to my analysis, finding optimal strategies for supply entities and bioconversion facilities has most strongly attracted the attention of researchers, while the investigation of policy mechanisms on SBSC systems ranks second in the existing literature. I observe that 79 publications address biomass feedstock supply problems, including biomass production (Heavey & Volk, 2016), land acquisition (Gonela et al., 2022), upstream flow rate analysis (Duarte et al., 2016; Leong et al., 2019) for forest- (Palander et al., 2018; Rogers et al., 2016; Saghaei et al., 2020) and agriculture-based residues (Aslaam et al., 2018; Gital & Bilgen, 2020; Taylor et al., 2013), energy crop procurement (Caldeira et al., 2019; Petridis & Grigoroudis, 2018; Shallo et al., 2020), and microalgae treatment (Nodooshan et al., 2018). In addition, various harvest planning decisions is investigated in the existing literature, such as harvesting automation (Lozano-moreno & Mar, 2019), and cost-emissions analysis (Nurariffudin et al., 2018) for sugarcane crops (Lozano-moreno & Mar, 2019), logging residues (She, 2020) and wheat straws (Galanopoulos et al., 2018), as well as forest-based timber (Chitawo et al., 2018). Additionally, inter-functional transportation applications have been broadly examined in 53 papers (Ekşioğlu et al., 2009; Guo et al., 2016; Mousavi Ahranjani et al., 2018; She, 2020).

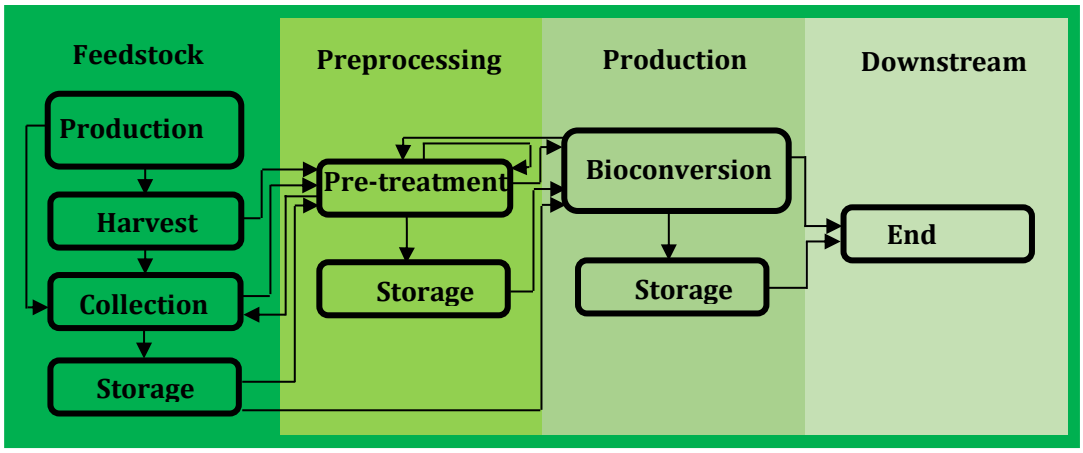

Figure 2.4. Operational interrelationships in biomass supply chains. (Block and arrow represent operation and transportation paths, respectively) [adopted from De Meyer et al. (2012)].

Table 2.3 lists the feedstock categories and final bioproduct classes studied in the reviewed biomass supply chain literature (Asia, 2020). Academic publications address various energy crops such as corn, wheat, sugarcane, palm oil, rapeseed oil, rubber seed oil, sunflower, Jatropha, sorghum, switchgrass, miscanthus, and safflower (F. Ye, et al., 2020a), forest-based biomass (Kittler et al., 2020), agricultural residues such as corn stover, mill residues, wheat straw, rice straw, cotton residues, barley straw, palm residues, and sugarcane residues (Razm et al., 2019), agriculture wastes (Vincevica-gaile et al., 2019), industrial wastes, especially paper-pulp and cooking oil disposals (Yong Zhang & Jiang, 2017), municipal solid wastes (Mohseni & Pishvaee, 2020), microalgae (Asadi et al., 2018), and marine biomass resources (Mulyati & Geldermann, 2017). In this context, energy crops, and forest-based intakes have been of particular interest, whereas less attention is given to waste resources that significantly affect natural ecosystems. Taking into account the biomass

conversion processes, my review classifies bioproducts into biofuel, i.e., pellets, ethanol, hydrogen, methanol, gasoline, biodiesel, biogas, bio-oil, vegetable oil, bio-syngas, bio-alcohols, bio-Fischer-Tropsch diesel, wood diesel, and renewable liquid methanol (Bijarchiyan et al., 2020), bioenergy (Mai-moulin & Visser., 2018), electricity (Gumte & Mitra, 2019), heat (Matopoulos et al., 2018), bio-chemicals (Saghaei et al., 2020), and biomaterial (Chazara et al., 2017). Among these categories, the exploration of biofuel supply chains is the center of academic research, while scholars also study bioenergy and electricity production frameworks in detail over the last two decades.

Table 2.3. The biomass and bioproduct type frequency in the reviewed literature.

Feedstock Type	Frequency	Bioproduct type	Frequency
Energy crops	105	Biofuel	257
Forest-based Biomass	95	Bioenergy	63
Agricultural residues	57	Electricity (Power)	59
Agriculture wastes	25	Heat	18
Industrial wastes	17	Bio-chemicals	3
Microalgae	13	Biomaterial	2
Municipal solid wastes	11	Multiple products	1
Marine biomass resources	1	Not Specified	49
Not Specified	114		

Table 2.4 indicates that decision levels in the reviewed publications intersect with different levels of analysis (Barbosa-póvoa et al., 2018). Most research (82 percent) study mesoscopic problems at the interaction of several operations in biomass supply chains. On the other hand, I observe that less attention is given to macroscopic models considering an industry-led perspective or the microscopic level concentrated on a single firm. Moreover, strategic decisions dominate the reviewed content, while operational problems have drawn less attention in my final reference pool.

Table 2.4. Joint distribution of the SBSC publications over the decision level and the level of analysis.

	Operational	Tactical	Strategic	Operational + Tactical	Operational + Strategic	Tactical + Strategic	Triple Aspects
Microscopic	7	1	22	0	0	3	1
Mesoscopic	27	65	63	17	7	177	12
Macroscopic	18	3	24	0	0	3	0

Among the 450 reviewed papers, 325 investigated network design problems in biomass supply chains. The transportation driver is the center of scholarly attention, with 294 transportation-based references, of which 118 publications study location problems. Attractive transportation policies and decisions explored in this context include shipping volume across the supply chain (Garofalo et al., 2020; Rahemi et al., 2020; Yong Zhang & Jiang, 2017), selection of transportation modes (Mousavi Ahranjani et al., 2018)(Gonela et al., 2022; Mousavi Ahranjani et al., 2020), fleet capacity (Axelsson et al., 2012; Yılmaz Balaman et al., 2019), as well as order frequencies required to distribute feedstocks and bioproducts (Ahmed & Sarkar, 2018). Moreover, 13 studies combine transportation and routing decisions in biomass supply chains (Nugroho & Zhu, 2019; Paolucci et al., 2016; Quddus et al., 2017). In a different research avenue, I identify 52 publications that account for inventory management and lot sizing frameworks (Gonela et al., 2022; Palander et al., 2018; Rabbani et al., 2020), where 49 integrate transportation strategies with inventory considerations. Surprisingly, only two publications exploring network design applications have addressed reverse supply chains over the past five years

(Galvez et al., 2015; Zhao et al., 2018), and both studies have incorporated waste management mechanisms in their formulation.

My findings reveal that 93 of the reviewed papers address production planning decisions. Critical decisions in this context include land use for bioenergy crop production (Nepal & Tran, 2019), biomass mixture from different feedstock types (Lauven et al., 2019), production quantity at preprocessing facilities (Halim et al., 2019; Saadati & Hosseininezhad, 2019), production quantity at biorefinery sites (Abriyantoro et al., 2019; Fattahi & Govindan, 2018; Saadati & Hosseininezhad, 2019), conversion and balance of materials (Hosseinalizadeh et al., 2019), the biomass processing capacity of biorefinery plants (Mousavi Ahranjani et al., 2018), mass balance considerations (Gao et al., 2019), limits of production capacity (Gao et al., 2019), as well as bioproduct shipments to demand centers (Mousavi Ahranjani et al., 2018). Moreover, multi-period production planning (Abriyantoro et al., 2019; Hosseinalizadeh et al., 2019; Saadati & Hosseininezhad, 2019) and effective technology selection (Díaz-Trujillo & Nápoles-Rivera, 2019; Harahap et al., 2019; Mousavi Ahranjani et al., 2020; Yılmaz Balaman et al., 2019) have been of particular interest. Besides these, 52 studies jointly consider production planning and network design problems, while 16 papers unify production planning and sourcing decision-making.

My content analysis also indicates that 31 studies explore the pricing problems of SBSCs, whereas 20 investigate joint pricing and network design strategies (Arabi et al., 2019; Benjamin, 2018; Mamun et al., 2020). Moreover, some researchers consider

pricing and risk management issues (Bruckman et al., 2018; F. Ye, et al., 2020a), and three publications explore pricing decisions combined with feedstock sourcing problems (Caldeira et al., 2019; F. Ye, et al., 2020a; F. Ye, et al., 2020b). Among four papers studying competition frameworks, two publications (Alaoui, 2020; F. Ye, et al., 2020b) address price competition in SBSCs, and Rahemi et al. (2020) and Wiens et al. (2019) explore competition in network design scenarios. Alaoui (2020) searches for optimal biodiesel prices outperforming classical diesel alternatives, and F. Ye, et al. (2020b) examine price competition instances between enterprises.

I observe a promising research stream in the literature centered on coordination and contracting strategies. These studies propose contract mechanisms such as protection price-subsidy and buyback-revenue sharing (Fan et al., 2019a; Tsao & Vu, 2019), principal-agent contract and quantity discount (Yang et al., 2018a), risk-sharing (Ye et al., 2018), and production cost-sharing (F. Ye, et al., 2020a). Four of these studies incorporate pricing decisions into the procurement stage (Fan et al., 2019; Tsao & Vu, 2019; Yang et al., 2018; F. Ye, et al., 2020a) while Bruckman et al. (2018) and F. Ye et al. (2018) integrate coordination contracts and production planning decisions, and F. Ye et al. (2020) account for planting decisions. Moreover, three studies explore integrating network design cases and transportation problems (Galanopoulos et al., 2020; Rahemi et al., 2020; Zheng et al., 2020), where Zheng et al., (2020) study reverse operations of waste cooking oil to produce biodiesel.

My content analysis shows that 37 papers address waste management applications, 11 of which study industrial cases considering waste cooking oil (Yang et al., 2020;

Zheng et al., 2020) and ash and biochar (Vincevica-gaile et al., 2019) as biomass feedstock inputs. In addition, nine papers investigate agricultural waste (Sarkar & Sarkar, 2020; Vlachokostas et al., 2020) such as livestock manure (Malladi & Sowlati, 2020), corn crop residues (Tiammee & Likasiri, 2020), and bagasse (Saadati & Hosseininezhad, 2019). Moreover, five articles explore municipal solid waste management centered on sewage sludge (Rabbani et al., 2020) and wastewater sludge (Mohseni & Pishvaee, 2020), and two studies concentrate on wood waste supply chains (Bais-Moleman et al., 2018; Paredes-Sánchez et al., 2018). From the conversion output perspective, represented in 22 papers, the most popular bioproduct produced from wastes is biofuel (Saadati & Hosseininezhad, 2019; Yilmaz Balaman & Selim, 2014; Zheng et al., 2020), followed by bioenergy (Varbanov et al., 2018; H. Zhang et al., 2014) and electricity production (Bijarchiyan et al., 2020; Mahjoub et al., 2020).

2.3.2. Sustainability development

In this section, I analyze the investigated materials from the sustainability development viewpoint. Figure 2.5 demonstrates the distribution of the economic, environmental, and social aspects in the investigated publications. I note that the number of studies considering the environmental aspect of sustainability is close to that of the economic pillar per year, representing the natural coexistence of ecological considerations and biomass business goals. In contrast, the social pillar has not received the same attention.

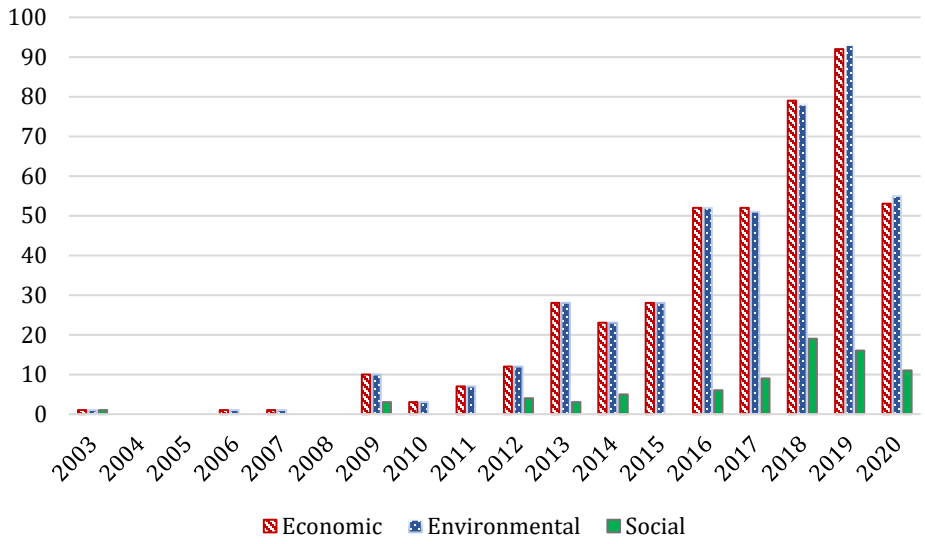

Figure 2.5. Distribution of the sustainability pillars in biomass supply chains publications over time.

Figure 2.6 shows the number of papers across the three sustainability dimensions, demonstrating that 16.6 percent of the review scope integrates all sustainability pillars in biomass supply chains. As depicted in Figure 2.6, none of the reviewed references exclusively study the economic aspect or the social paradigm.

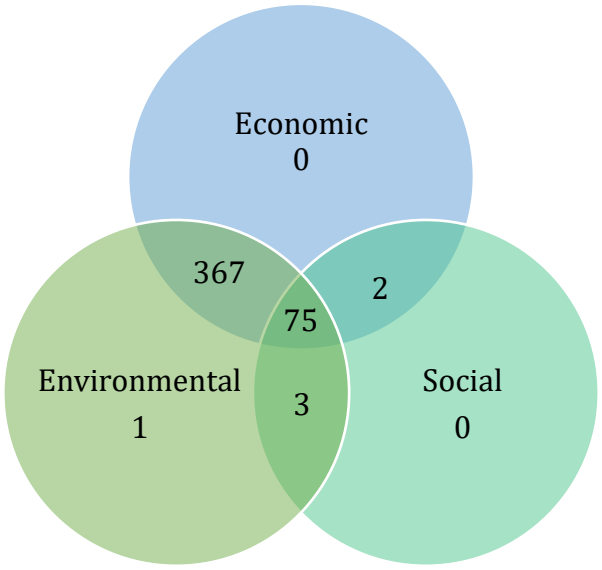

Figure 2.6. The number of the investigated SBSC papers in each pillar of sustainability.

Table 2.5 demonstrates both environmental and social dimensions studied in the reviewed publications. More than half of the papers investigate GHG emissions indicators focusing on climate change and air pollution concerns. On the other hand, little attention has been paid to the environmental aspects of water, soil, and land. As shown in Table 2.5, 67 studies adopt the life cycle assessment approach to quantify ecological requirements in the biomass sector. On the other hand, job creation has been broadly considered in the socially-consensus SBSC literature (54 papers). Nevertheless, the existing SBSC literature pays insufficient attention to social indicators, and most studies primarily prioritize the environmental pillar in their decision-making.

Table 2.5. Environmental and social indicators studied in the reviewed publications.

Environmental pillar	**Frequency**	**Social pillar**	**Frequency**
GHG emissions	298	Job creation	54
Life cycle assessment	67	Safety	10
Indirect Environmental benefit	61	Social services (including leisure and health matters)	10
Land use (including land-use changes related to bioenergy feedstock production)	32	Food security	7
Soil quality	20	Poverty reduction	7
Not specified	19	Child labor matters	2
Water use and efficiency	14	CSR investment	2
Water resources quality	11	Consumer surplus	1
Other emissions (non-GHG air pollutants, including air toxics)	10	Community improvements	1
Waste reduction	9		
Biological diversity	5		
Logistical distance to ecological units	1		

My analysis shows that 81 papers address the role of governmental policies, programs, and regulations in the SBSC context. Table 6.1 in the Appendix provides a complete list of the references that explore such policies, among which 14 papers address incentive-based programs. Governments offer these incentives, particularly in the energy sector, to motivate bioenergy producers (Mohamed Abdul Ghani et al., 2020) or renewable-source consumption facilities (Yazan, Fraccascia, et al., 2018; Yılmaz Balaman et al., 2019; N. Zhao & You, 2019) to adopt greener initiatives. Moreover, some papers investigate financial incentives for pioneering firms to replace first-generation biomass feedstocks with second-generation sources (Aslaam et al., 2018; Haji Esmaeili et al., 2020; Rivera-Cadavid et al., 2019). Offering price incentives is another strategy to promote sustainability in biomass supply chains. Wen & Zhou, (2018) explore offering price incentives to either straw producers or buyers, and 28 papers show that providing such incentives for the bioelectricity sector would increase biodiesel consumption and production.

Moreover, 22 reviewed studies explore governmental subsidy programs supporting biofuel producers, such as direct payments, loans, and tax credits (Wang et al., 2017). F. Ye, Cai, et al. (2020), and Fan et al. (2019) explore such mechanisms for farmers and bioenergy producers. F. Ye, et al. (2020b) address a poverty alleviation program, a social welfare program, and a subsidy rate for loan agreements in the bioenergy sector. Touš et al. (2011) address subsidies that target electricity production from renewable feedstock sources. Pavlou et al. (2016) show that subsidies for biomass production lower the price of biomass. Bajgiran et al. (2019) investigate subsidy prices for growing and refining energy crops to the farmer, while Kuo et al. (2019)

develop a suitable subsidy pricing program considering technological improvements and market demands. Tan et al. (2017) study incentivizing schemes aiming at biomass-based power plants by adjusting the price of on-grid electricity, and Moncada et al. (2019) investigate capital investment subsidies. The government finances a share of the whole capital to construct a biojet fuel firm.

My analysis shows that 24 reviewed publications address governmental tax policies for the sustainable management of biomass supply chains, focusing on carbon tax charges and credits. Eleven papers study carbon tax rates where a government aims to impose a penalty per unit of carbon emission to different actors of the proposed biomass supply chain (Alizadeh et al., 2019; Giarola et al., 2020; Gonela, 2018). Ahmed & Sarkar, (2019) study the employment of the carbon tax policy on hazardous emissions in various farm activities, such as the harvesting and transporting of raw materials and biofuels. On the other hand, credit schemes offer tax exemption policies supported by governments, thereby improving sustainability performance and reducing GHG discharges (Iliopoulos & Rozakis, 2010; Mutenure et al., 2018). Sánchez-Bautista et al. (2017) show that a significant tax credit increases the number of forest plantations, thus improving the revenue of biomass supply chains. In their model, the tax credit amount for biorefineries is set higher than that of refineries. Finally, some papers study penalty and credit taxation strategies in their models (Malladi & Sowlati, 2020; Palak et al., 2014; Park et al., 2019).

Several studies explore other regulation programs; Dharmawan et al. (2020) investigate a mandatory certification policy for the entire value chain of biodiesel

production from oil palm to implement sustainability initiatives. Kittler et al. (2020) address sustainable sourcing programs, including certifications for forest management and chain of custody. Besides these, Buliga & Nichiforel, (2019) evaluate a voluntary forest certification program and stringent legal policies. In the work of Allameh et al. (2019), the government imposes a Renewable Identification Number mechanism to promote biofuel production as a replacement for conventional gasoline. Some publications study air pollution regulations considering carbon trading systems (Y. Bai et al., 2016; Giarola, Shah, et al., 2012; Memari et al., 2018; Touš et al., 2011), maximum and minimum allowable amounts of GHG emissions (Hombach et al., 2016), and penalties set for air pollution caused by biofuel production and fossil fuel consumption (Azadeh & Vafa Arani, 2016). Furthermore, regarding ground use and environmental regulations, Jeong & Ramírez-Gómez (2018) locate biomass plants considering such government legislation, while Howard et al. (2009) investigate ecological protection and a resilient energy system using an economic model. Palander et al. (2018) study policy decisions regarding energy-efficiency regulations and sustainable forest use, and Cantegril et al. (2019) investigate the harvest schedule of a wood supply model developed by government planners. My analysis indicates that almost half of the publications considering governmental regulations are introduced in the forestry sector.

Only 16 percent of previous publications address the effects of these programs in practice, where improper processes of biomass feedstock resources due to lack of adequate regulations can cause various environmental and health issues (Mohamed Abdul Ghani et al., 2020; N. Zhao & You, 2019). Moreover, supporting local economies

through incentive programs can lessen supply, market price, and demand uncertainties, increasing bioproducts' production (Yılmaz Balaman et al., 2019). For instance, the German government's proper financial support system leads to the rapid growth of biogas plants in Germany (N. Zhao & You, 2019). All in all, supporting economies by implementing comprehensive governmental and international policies is highly recommended.

2.3.3. Modeling methodology

My review findings from a modeling perspective are provided in this section. Table 2.6 represents the frequency of modeling approaches in the selected SBSC publications. These approaches are classified into four main categories: mathematical programming, multi-criteria decision-making, simulation analysis, and systematic modeling.

The results show that mixed-integer programming is the most popular quantitative technique used in the literature, applied in 214 studies of the reviewed publications (see, for example, Park et al., 2019; Rahemi et al., 2020). In total, 269 papers apply deterministic approaches, while 136 publications work in a stochastic setting. Such studies investigate yield uncertainty (F. Ye, et al., 2020b), lead time uncertainty (Nugroho & Zhu, 2019), transportation cost uncertainty (Flores Hernández et al., 2020), price uncertainty (Arabi et al., 2019), demand uncertainty (He-Lambert et al., 2019), and information uncertainty (Geng et al., 2020). Stochastic programming is an efficient tool in the literature to tackle this source of complexity, applied in 46 papers (Nguyen & Chen, 2018; Quddus et al., 2017). Other methods adopted to cope with stochasticity factors include epsilon constraint in 27 papers (Ahmed & Sarkar, 2019;

Babazadeh et al., 2017), fuzzy logic in 23 articles (Ahmed & Sarkar, 2019; Jeong & Ramírez-Gómez, 2018), robust optimization is in 18 studies (Elisabeth et al., 2018; Gilani & Sahebi, 2020), and chance constraint is used in four references (Gital & Bilgen, 2020; Saghaei et al., 2020). Moreover, multi-objective modeling is applied more frequently than single-objective structures, mostly centered on epsilon constraint and goal programing methods. Also, three papers study risk management based on the CVaR measure (Kashanian et al., 2020; F. Ye, Cai, et al., 2020; F. Ye, et al., 2020a), 18 papers have applied predictive models (Garofalo et al., 2020; Smith et al., 2018).

Table 2.6 also represents the distribution of multi-criteria decision-making approaches, where AHP and ANP are the most popular models (Wheeler et al., 2017; Woo et al., 2018). Other techniques in this category are BWM (Akbarian-Saravi et al., 2020; Kashanian et al., 2020), DEA (Arabi et al., 2019; Eguchi et al., 2015), DEMATEL (Jeong & González-Gómez, 2020; Jeong & Ramírez-Gómez, 2018), TOPSIS (J. Y. Lim et al., 2020; Rabbani et al., 2018), SWOT (Fernández-González et al., 2020; Naeini et al., 2020), Electre (Zheng et al., 2020), as well as VIKOR (Vasković et al., 2015). There is only one study (Fernández-González et al., 2020) that jointly applies AHP and SWOT methods to explore the competitive advantages of biogas production.

In the simulation category, system dynamics has drawn particular attention in the literature (Trujillo-Mata et al., 2018; Zahraee et al., 2019). In addition, scholars apply Monte Carlo (Mamun et al., 2020; Yazan et al., 2016), discrete event (Fernandez-Lacruz et al., 2020; Muresan et al., 2013), spreadsheet analysis (Finnan & Styles, 2013;

Mauro et al., 2018), agent-based model (Caldeira et al., 2019; Moncada et al., 2019; Yazan, Fraccascia, et al., 2018), and business process simulation (Galanopoulos et al., 2020) techniques to study SBSC applications. Moreover, several systematic methods are applied in the literature to examine SBSC instances, including financial analysis (Babazadeh et al., 2017; Yun et al., 2020), life cycle analysis (Ghosh & Bakshi, 2019; Yilmaz Balaman & Selim, 2014), structural analysis (C. H. Lim et al., 2019; Mohseni & Pishvaee, 2020), descriptive statistics (Bruckman et al., 2018; Mai-moulin & Visser, n.d.), software-based (Boldrin et al., 2016; Sahoo et al., 2018), techno-economic (Rincon et al., 2019; Yanan Zhang et al., 2014), DSS (Lam et al., 2013; Van Holsbeeck & Srivastava, 2020), input/output analysis (Aviso et al., 2011; Yazan, Cafagna, et al., 2018), as well as statistical hypothesis testing (Garofalo et al., 2020). The structural analysis includes 16 game-theoretic studies targeting equilibrium points (Fan et al., 2019; F. Ye, et al., 2020a) and 12 single-player optimization applications exploring closed-form solutions (F. Ye, et al., 2020a; F. Ye, et al., 2020b).

Table 2.6. The frequency of modeling approaches proposed in the SBSC publications.

Mathematical programming	Mixed-integer programming (214), Linear programming (189), Multi-objective programming (173), Stochastic programming (46), Non-linear programming (45), Epsilon constraint (27), Robust optimization (18), Goal programming (6), P-graph (6), Chance constraint (4), CVaR (3), Constraint programming (1)
Multi-criteria decision-making	AHP/ANP (13), Best worst method (7), DEA (6), DEMATEL (2), TOPSIS (2), SWOT (2), Electre (1), VIKOR (1)
Simulation modeling	System dynamics (12), Monte Carlo (10), Discrete event (5), Spreadsheet analysis (5), Agent-based model (3), Business process simulation (1)
Systematic modeling	Financial analysis (56), Life cycle analysis (47), Structural analysis (28), Descriptive statistics (25), Software-based (22), Techno-economic (16), Decision support system (13), Input/Output analysis (9), Regression analysis (18), Statistical hypothesis testing (1)

My analysis also reveals that 22 papers address meta-heuristic methods, and only three publications study heuristic algorithms. Some of the applied meta-heuristic approaches are genetic algorithm (Ayoub et al., 2009; Saghaei et al., 2020), neural network (Akbarian-Saravi et al., 2020; Sahoo et al., 2018), particle swarm optimization (Asadi et al., 2018; Kesharwani & Sun, 2018), tabu search (Aboytes-Ojeda et al., 2020), simulated annealing (Aboytes-Ojeda et al., 2020), and NSGA-ll (Asadi et al., 2018). Moreover, a few studies investigate data-driven frameworks for biomass supply chains. For instance, Geng et al. (2020) propose combining a clustering algorithm and rough set theory in a biofuel supply chain.

2.4. Literature review on contract design

Ye et al. (2020) propose a production cost-sharing contract for a cassava-based bioethanol supply chain and use a game-theoretic approach to explore decisions considering yield uncertainty and competition between players. Ye et al. (2018) model three types of coordination mechanisms for a biofuel supply chain: a biofuel producer and farmers in a random yield environment. The coordination contracts are over-production risk-sharing, under-production risk-sharing, mixed contracting, and an asymmetric Nash bargaining model. Tsao & Vu. (2019) investigate a network design problem for an intelligent power supply chain using differential pricing and buy-back mechanisms to maximize the profit of the companies and users. Decentralized and centralized models using a non-linear optimization algorithm are examined. Fan et al. (2019) study centralization and coordination in a solid biomass fuel supply chain, including multiple suppliers that face random supply intakes and stochastic demand patterns. They apply price subsidies, market protection price

contracts between the manufacturer and farmers, and the revenue-sharing contract with buyback between the manufacturer and the middleman. Yang et al. (2018) study a reverse supply chain of waste cooking oil into biofuel under asymmetric cost information. They explore a principal-agent and a quantity discount contract and optimal contract parameters of the bio-firm and the recycler. Yang et al. (2020) use the principal-agent contract to analyze two types of government subsidy, including raw material price subsidy and finished product sale subsidy, to encourage recycling activities under the situation that the waste cooking oil conversion rate is private information.

2.5. Research gap and questions

As discussed before, the digitization of paper-based media, low-cost global competition from developing nations, and an excess global supply of their goods have contributed to a decline in demand for conventional pulp and paper products in the Canadian pulp and paper sector during the last decade. Therefore, establishing effective ways to manage demand challenges in the pulp and paper sector is highly important. In addition, sustainability issues, specifically environmental aspects, are fundamental these days. Supply chain participants must consider environmental and social problems and investigate cost-effective regulatory approaches to execute sustainability-driven plans. Overall, given the uncertainty in demand for the pulp and paper sector, improving the regulation-based sustainability of Canadian applications is critical, which is the focus of this study.

None of the reviewed studies in the previous subsections addresses the sustainability of the pulp and paper sector in a game-theoretic framework. Moreover, the previous

studies did not consider sustainability programs such as the cap-and-trade mechanism and the government's role in subsidizing the players. Unlike the studies above, this thesis aims to design a contract between the local government and a pulp and paper mill in a sustainable forest-based biomass supply chain. In the proposed SBSC, the government establishes a cap-and-trade mechanism and subsidy program to promote sustainability. Accordingly, pulp and paper mills aim to decrease her GHG emission. Thus, she invests in technology improvement, which incurs a cost. The investment level of the pulp and paper mill linearly decreases the GHG emission. In such a case, the government provides subsidy programs to incentivize the pulp and paper mill. However, the demand level of the pulp and paper mill is her private information that the government should consider in the offered subsidy program. Therefore, he applies a principal-agent contract, widely used in the literature on asymmetric information (Yang et al., 2018b). Considering her asymmetric demand information, this thesis aims to effectively design contract parameters for the government's subsidies to the mill. Accordingly, my research questions are as follows:

- What is the pulp and paper mill's optimal technology investment level?
- How can the government design an effective contract under asymmetric demand information which satisfies all SBSC members?
- How can the government ensure the truth-telling of the pulp and paper mill?
- How can the government contribute to promoting sustainable pulp and paper production?

Chapter 3. Modeling

This study explores an SBSC in the pulp and paper industry. A forest supplier provides pulp logs. The flow of pulp logs to the mill under consideration is excluded meaning that the forest supplier's role in Figure 1.2 is not considered in this model. The pulp and paper mill and the government are the decision-makers of the SBSC. The local government actively accounts for sustainability concerns and strategies. To improve sustainability, the government applies a cap-and-trade mechanism by setting emissions allowance of GHG emitted by the pulp and paper factory, which allows other emissions to be purchased from firms that have not fully utilized their allowable amount. This model excluded the other firms in the trading market. The pulp and paper mill should improve technology to reduce GHG emissions. This technology improvement incurs costs to the pulp and paper mill, affecting its decision on technology improvement. The pulp and paper mill decides on technology investment level I, with the technology improvement cost of investment level, $C(I)$, given in Equation 3.1 (Yang et al., 2021). In such a case, the local government provides subsidy programs (S, T) to incentivize the pulp and paper mill to invest more and reduce GHG emissions. Local government's subsidy for compensation of the technology improvement cost is denoted by S, and the government's transfer payment to the mill is indicated by T.

$$C(I) = \frac{1}{2}\beta I^2 \tag{3.1}$$

The pulp and paper mill's demand pattern is private information in the SBSC. It is assumed that the entire demand must be met. Using his observations in the past, the

local government can quantify the probability that the production company's demand level could be categorized as low or high. Note that a more elevated pulp and paper demand results in more carbon emission, which needs more technology improvement investment to reduce the mill's carbon trading costs of the cap-and-trade mechanism. In such a case, the government offers a subsidy program and transfer payment using a principal-agent contract (S, T), based on the asymmetric information on the demand level to encourage the pulp and paper company to boost up its green investments, thus, curbing environmental consequences. Meanwhile, the local government should try to ensure the truth-telling of the mill about the demand pattern. Model parameters and decision variables are provided in Table 3.1.

Table 3.1. Model parameters and variables.

Parameter	**Description**
$i = l, h$	Type of pulp and paper demand (l: low; h: high)
d_i	Demand of type-i pulp and paper mill
p	The probability that the company has less demand (estimated by government)
$C(I_{ij})$	The technology improvement cost of investment level I_{ij} when type-i mill chooses type-j
r	Selling price of paper ($ per metric ton)
c	Cost of paper production ($ per metric ton)
α	Carbon price ($ per metric ton)
e_1	The regular carbon emission (metric tons)
e_2	The efficiency of the mill's technology investment in carbon emission reduction
e_3	Cap Adjustment Factor
Cap	The maximum allowable amount of carbon dioxide (metric tons)
β	Cost coefficient of technology improvement investment
u	Unit of social utilities that each unit of carbon emission reduction provides to the society ($)
Variables	**Description**
I_{ij}	The type-i pulp and paper mill's technology investment level when she announces type-j
S_j	Government subsidy for compensation of technology improvement costs to the mill when she announces type-j
T_j	Government transfer payment to the mill when she announces type-j

The demand pattern is private information. Based on the previous reports, the local government knows that demand is low with the probability p, and the pulp and paper is a high-demand mill with the probability $1-p$. Therefore, the government's demand estimation is a random variable following the Bernoulli distribution (see Equation 3.2). The two-point distribution is commonly used in the existing contracting literature to extract the structural properties of the proposed regulatory mechanisms (Lei et al., 2015).

$$d = \begin{cases} d_l, & \text{with probability } p, \\ d_h, & \text{with probability } 1-p. \end{cases} \tag{3.2}$$

Moreover, the government imposes a cap-and-trade mechanism with the maximum allowable amount of carbon emission, $Cap = e_3 d_i$, and carbon price, α, to encourage the mill to invest more in emission reduction technology improvement. The total amount of emission per unit pulp and paper demand is a decreasing function of the mill's technology investment level shown in Equation 3.3 (Q. Bai et al., 2017). Technology improvement incurs costs to the mill. In such a case, determining the optimal investment level is highly important for all the biomass supply chain members, the environment, and society. The government suggests a principal-agent contract (S, T) to the mill in which the government is the agent and the mill is the principal entity due to her accessibility to perfect information. The game ends if the mill refuses to participate in the contract. Otherwise, the mill chooses the contract based on her demand type and decides on her technology improvement investment level.

$$Emission = \left(e_1 - e_2 I_{ij}\right) d_i \tag{3.3}$$

The mill's profit function is provided in Equation 3.4. The government suggests a menu of principal-agent contracts to the pulp and paper mill $(S_i, T_i), i, j \in \{l, h\}$, depending on the type of mill's demand. In the suggested contract, the government ensures the pulp and paper mill's truth-telling about her demand type (Kolb, 2018), which will be characterized in the optimization model below. Moreover, the second subscript j demonstrates the type of demand announced by the mill. A type i pulp and paper mill announces to be j, meaning that she selects the contract $(S_j, T_j), i, j \in \{l, h\}$. Therefore, the profit function of the mill is $\pi_{ij}^{p}(I_{ij})$. The first term in Equation 3.4 accounts for the mill's exogenous, marginal profit and the proposed subsidy. The second expression represents the cap-and-trade cost/benefit based on the emission amount of the mill. The last term represents the final investment cost of the mill, including the government's subsidy for technology improvement for carbon emission reduction.

$$\pi_{ij}^{p}(I_{ij}) = (r + T_j I_{ij} - c)d_i - \alpha\left(\left(e_1 - e_2 I_{ij}\right)d_i - e_3 d_i\right) - (1 - S_j)(\tfrac{1}{2}\beta I_{ij}^2), i, j \in \{l, h\}$$

$$\pi_{ll}^{p}(I_{ll}) = (r + T_l I_{ll} - c)d_l - \alpha\left((e_1 - e_2 I_{ll})d_l - e_3 d_l\right) - (1 - S_l)(\tfrac{1}{2}\beta I_{ll}^2)$$

$$\pi_{lh}^{p}(I_{lh}) = (r + T_h I_{lh} - c)d_l - \alpha\left((e_1 - e_2 I_{lh})d_l - e_3 d_l\right) - (1 - S_h)(\tfrac{1}{2}\beta I_{lh}^2)$$

$$\pi_{hl}^{p}(I_{hl}) = (r + T_l I_{hl} - c)d_h - \alpha\left((e_1 - e_2 I_{hl})d_h - e_3 d_h\right) - (1 - S_l)(\tfrac{1}{2}\beta I_{hl}^2)$$

$$\pi_{hh}^{p}(I_{hh}) = (r + T_h I_{hh} - c)d_h - \alpha\left((e_1 - e_2 I_{hh})d_h - e_3 d_h\right) - (1 - S_h)(\tfrac{1}{2}\beta I_{hh}^2) \quad (3.4)$$

In total, four different scenarios may happen for the pulp and paper mills based on their actual type of demand, represented by $i \in \{l, h\}$, and the claimed type of demand, represented by $j \in \{l, h\}$. Thus, the combinations are ll, lh, hl, hh. These four scenarios

are provided in Equation 3.4. For instance, the first item related to ll, means that the pulp and paper mill is low-demand, and based on the proposed subsidy contract, she would choose to be truthful and announce that she is low-demand. Contrary to the previous example, the lh scenario represents the situation that the proposed subsidy contract is not satisfied with the low-demand mill, and she decides to announce high-demand. The hl and hh scenarios can be explained similarly.

The government utility function is indicated in Equation 3.5. Implementing the principal-agent contract, the government aims to realize the actual type of the mill's demand and optimize the social utilities of carbon emission reduction. The first term of Equation 3.5 shows the social utility resulting from technology improvement investment. Please note that the government estimates the unit of social utilities that each unit of carbon emission reduction provides to the society and it is based on dollars. The next term is the government's costs of subsidy rate per unit and transfer payment to the mill. Moreover, the government cannot access true information about the pulp and paper mill demand. Therefore, the government aims to maximize his expected utility function, given in Equation 3.6 and extended in Equation 3.7.

$$\pi_i^g(S_i, T_i) = ue_2 I_{ii} d_i - T_i I_{ii} d_i - \frac{1}{2} S_i \beta I_{ii}^2, i \in \{l, h\} \tag{3.5}$$

$$\pi^g(S_i, T_i) = p\pi_l^g + (1-p)\pi_h^g$$

$$\pi^g(S_i, T_i) = p\left(ue_2 I_{ll} d_l - T_l I_{ll} d_l - \frac{1}{2} S_l \beta I_{ll}^2\right) + \tag{3.6}$$

$$(1-p)\left(ue_2 I_{hh} d_h - T_h I_{hh} d_h - \frac{1}{2} S_h \beta I_{hh}^2\right) \tag{3.7}$$

The government's proposed principal-agent contract should simultaneously satisfy the mill's expectations and induce the mill's truth-telling about the final demand shown in Equation 3.8. Participation constraints IRL and IRH satisfy the positivity of the mill's profit. Moreover, incentive compatibility constraints ICL and ICH ensure the truth-telling of the mill. Consecutively, the leader government's optimal decisions underscored by the principal-agent contract variables can be derived using the Karush–Kuhn–Tucker conditions. Finally, using backward induction, the pulp and paper mill's optimal strategy measured by the technology investment level can be obtained in the follower (following?) subproblem. Figure 3.1 shows the sequence of decisions in the proposed SBSC model.

$$\max\ \pi^g(S_i, T_i) = p\left(ue_2 I_{ll} d_l - T_l I_{ll} d_l - \frac{1}{2} S_l \beta I_{ll}^2\right) + (1-p)\left(ue_2 I_{hh} d_h - T_h I_{hh} d_h - \tfrac{1}{2} S_h \beta I_{hh}^2\right)$$

$subject\ to$:

$$IRL \qquad (r + T_l I_{ll} - c) d_l - \alpha\big((e_1 - e_2 I_{ll}) d_l - e_3 d_l\big) - (1 - S_l)(\tfrac{1}{2}\beta I_{ll}^2) \geq 0$$

$$IRH \qquad (r + T_h I_{hh} - c) d_h - \alpha\big((e_1 - e_2 I_{hh}) d_h - e_3 d_h\big) - (1 - S_h)(\tfrac{1}{2}\beta I_{hh}^2) \geq 0$$

$$ICL \qquad (r + T_l I_{ll} - c) d_l - \alpha\big((e_1 - e_2 I_{ll}) d_l - e_3 d_l\big) - (1 - S_l)(\tfrac{1}{2}\beta I_{ll}^2) \geq (r + T_h I_{lh} - c) d_l - \alpha\big((e_1 - e_2 I_{lh}) d_l - e_3 d_l\big) - (1 - S_h)(\tfrac{1}{2}\beta I_{lh}^2)$$

$$ICH \qquad (r + T_h I_{hh} - c) d_h - \alpha\big((e_1 - e_2 I_{hh}) d_h - e_3 d_h\big) - (1 - S_h)(\tfrac{1}{2}\beta I_{hh}^2) \geq (r + T_l I_{hl} - c) d_h - \alpha\big((e_1 - e_2 I_{hl}) d_h - e_3 d_h\big) - (1 - S_l)(\tfrac{1}{2}\beta I_{hl}^2) \qquad (3.8)$$

According to the backward induction, the first step is to find the pulp and paper mill's technology investment level. Based on the first-order condition, the pulp and paper mill's optimal technology investment level is as follows:

$$I_{ij} = \frac{(\alpha e_2 + T_j)d_i}{(1-S_j)\beta}, i, j \in \{l, h\} \quad (3.9)$$

By substituting (3.9) into the principal-agent contract design problem (3.8), the equilibrium solution for the local government can be derived. Therefore, equilibrium strategies of the pulp and paper mill and the local government are provided in Propositions 1 and 2.

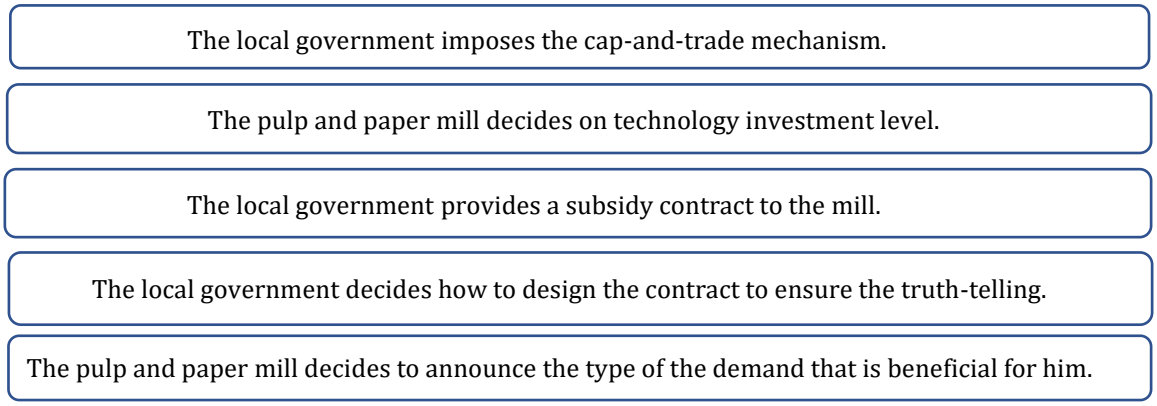

Figure 3.1. The visualization of the sequence of decisions in the biomass supply chain model

Proposition 1. a) If $\alpha(e_1 - e_3) + c - r \geq 0$ and $d_l \geq \frac{\sqrt{2\beta d_l(\alpha(e_1-e_3)+c-r)}}{e_2(\alpha+u)}$, the first solution set of government's subsidies are:

$S_l = 0$

$S_h = 0$

$$T_l = \frac{-\alpha e_2 d_l + \sqrt{2\beta d_l(\alpha(e_1 - e_3) + c - r)}}{d_l}$$

$$T_h = 0.5e_2(u - \alpha) \tag{3.10}$$

By substituting (3.10) into (3.9), the pulp and paper technology investment level can be derived as:

$$I_{ll} = \frac{\sqrt{2\beta d_l(\alpha(e_1 - e_3) + c - r)}}{\beta}$$

$$I_{lh} = \frac{0.5e_2 d_l(\alpha + u)}{\beta}$$

$$I_{hl} = \frac{d_h\sqrt{2\beta d_l(\alpha(e_1 - e_3) + c - r)}}{\beta d_l}$$

$$I_{hh} = \frac{0.5e_2 d_h(\alpha+u)}{\beta} \tag{3.11}$$

Proposition 2. b) If $\alpha(e_1 - e_3) + c - r \geq 0$ and $d_h \geq \frac{2\sqrt{2\beta d_h(\alpha(e_1-e_3)+c-r)}}{e_2(\alpha+u)}$, the local government's second subsidy strategies are:

$$S_l = 0$$

$$S_h = 0$$

$$T_l = 0.5e_2(u - \alpha)$$

$$T_h = \frac{-\alpha e_2 d_h + \sqrt{2\beta d_h(\alpha(e_1-e_3)+c-r)}}{d_h} \tag{3.12}$$

By substituting (3.12) into (3.9), the pulp and paper technology investment levels are as follows:

$$I_{ll} = \frac{(0.5e_2(\alpha + u))d_l}{\beta}$$

$$I_{lh} = \frac{d_l\sqrt{2\beta d_h(\alpha(e_1 - e_3) + c - r)}}{\beta d_h}$$

$$I_{hl} = \frac{0.5e_2 d_l(\alpha + u)}{\beta}$$

$$I_{hh} = \frac{\sqrt{2\beta d_h(\alpha(e_1 - e_3) + c - r)}}{\beta} \quad (3.13)$$

The proofs of these two propositions are provided in the Appendix. Note that the local government subsidy for compensation of technology improvement cost to both pulp and paper mills is zero. Solving the model suggests that the transfer payment subsidy works for all players of the SBSC in the principal-agent contract. Only the transfer payment type of subsidy helps the local government to convince the pulp and paper mill to tell the truth about her demand. According to the results of the decision variables, the subsidies, and the pulp and paper technology investment levels, the local government's estimation of the low or high demand affects the decision variables. Therefore, analyzing the impact of the local government's demand estimation on decision variables is essential. The next chapter is provided to numerically investigate the model's solution in different amounts of demand estimation.

Chapter 4. Numerical Analysis

This section numerically analyzes the studied SBSC decisions, profits, and sustainability measurements under different circumstances. According to Equation 3.1, the government's demand estimation is a binary variable. Primary indicators of the government's decisions include average demand (the μ parameter of the demand distribution) and uncertainty associated with asymmetric information (quantified by the σ^2 of the demand distribution), as follows:

$$\mu = pd_l + (1-p)d_h \tag{4.1}$$

$$\sigma^2 = p(1-p)(d_h - d_l)^2 \tag{4.2}$$

The analysis explores the effects of these factors (μ, σ^2) on the government subsidy program and utility function, the pulp and paper companies' investment levels and profits, and sustainability measurements. For numerical analysis, the following model parameters are considered:

$$p = 0.7, r = 600, c = 598, \alpha = 50, e_1 = 0.942, e_2 = 0.08, e_3 = 0.888, \beta = 10000000, u = 100,$$

which guarantees both mills' positive investment levels and profits. According to these parameters, the first solution's conditions are met. Notice that my conclusions about the effects of average demand and uncertainty level on the results of the analysis would not be impacted by different values of the parameters mentioned above.

4.1. Impacts of average estimating demand

This section investigates the effect of the government's average demand estimate on the model variables, profits, and sustainability indicators. Note that the level of

demand uncertainty σ^2 is fixed in these analyses. Figure 4.1. shows the effect of average demand, μ, on SBSC's decision variables. Figure 4.1. (a) depicts the impact of the average estimation of demand, μ, on the government's subsidy plan, T_l and T_h. As the subsidy policies S_l and S_h are both zero based on the model solution, they are not included. Figure 4.1. (b) illustrates the effect of average demand, μ, on the pulp and paper mill's decision variable, I_{ll} and l_{hh}. Notably, the goal of my SBSC subsidy program is to ensure that the pulp and paper mill is truthful about his demand level, and the Lagrange model determines the subsidy levels so that the pulp and paper firm will be honest. Therefore, only the investment levels of truth-telling scenarios, I_{ll} and l_{hh}, are analyzed in this chapter.

According to Figure 4.1 (a), an increase in the average demand lowers the transfer payment subsidy for the low pulp and paper mill type, while the subsidy for the high type remains constant. Figure 4.1 (b) demonstrates that the level of technology investment in both types of pulp and paper mills would rise as the government's estimation of the average demand increased. Once the average demand rises, the level of technology investment in both types of pulp and paper rises even when the government's subsidy either declines or remains constant. The company's GHG emissions increase by growing demand, necessitating further investment. Although the government knows that a transfer payment subsidy would encourage the mills to spend more, it declines the subsidy. I need to explore each SBSC party's profitability to determine if this tactic is effective.

Figure 4.2 shows the impact of increasing the government's average demand estimation on the profitability of all SBSC players. Again, as I ensure that both types of pulp and paper mills will be honest, only the profits of truth-telling cases are investigated (In Figure 4.2, profits are shown as $\pi_{ll}^{p}(I_{ll}) = Profit\ ll, \pi_{hh}^{p}(I_{hh}) = Profit\ hh$). This figure demonstrates that my concern about the mill's profits is misplaced. Therefore, the suggested model enables the local government to control its expenditures and choose an appropriate subsidy strategy. The low type of pulp and paper's profit is almost zero, meeting the model's constraints. Also, the high-demand profit is increasing, although her subsidy is fixed, and she is investing more in technology to drop GHG emissions. Again, it demonstrates that the local government's subsidy approach met the expectations of all SBSC players.

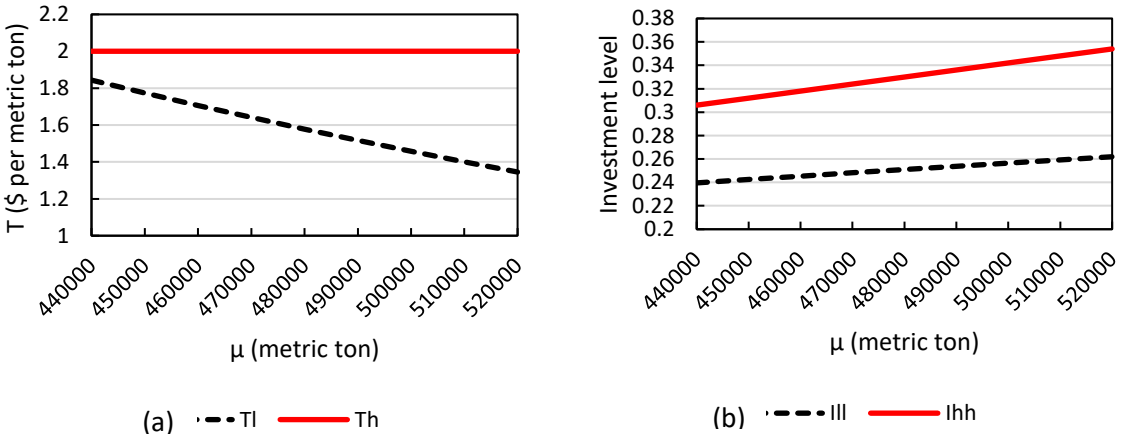

Figure 4.1. Impact of μ on subsidy T_j and investment level I_{ij}.

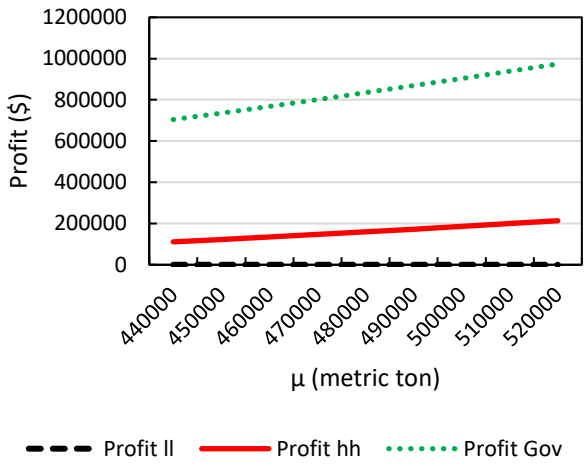

Figure 4.2. Impact of μ on profits of each SBSC party.

In the following, I will analyze the efficiency of the proposed subsidy strategy on the sustainability aspect of the SBSC in the presence of the cap-and-trade regulatory system. I evaluate the effect of the subsidy program on the GHG emission before and after subsidy and cap-and-trade for - and high-high-type pulp and paper mills in Figures 4.3 (a) and (b), respectively. I refer to the GHG emission before the subsidy as the primary emission in Equation 4.3 and the GHG emission after the subsidy as the secondary emission in Equation 4.4; therefore, the amount of reduced emission is the difference between the primary and the secondary emission in Equation 4.5. According to Figure 4.3, both pulp and paper mills reduce GHG emissions under the subsidy program, but the secondary emitted GHGs are still over the maximum permissible levels, which are shown as Cap ll and Cap hh in Figure 4.3. Taking the examples of the first and last points in Figure 4.3. (a), The low-demand mill's primary and secondary emissions are 386,220 and 378,361, while the cap is 364,080 for the minimum point of average estimating demand. Moreover, the primary and secondary

emissions of the high-demand type of mill are 480, 420 and 467,935.2, while the cap is 452,880 in Figure 4.3. (b) for the minimum point of average demand.

Primary emission: $e_1 d_l$ (4.3)

Secondary emission: $e_2 I_{ll} d_l$ (4.4)

Reduced emission = Primary emission- Secondary emission: $(e_1 - e_2 I_{ll}) d_l$ (4.5)

Figure 4.4 illustrates the exact amount (a) and percentage of reduced emissions (b) following the local government's implementation of the subsidy program so that the difference may be comprehended with more clarity. It shows that in the minimum point of average demand, the reduced GHG emissions for the low-demand and high-demand pulp and paper mills are 7,858 and 12,484, respectively.

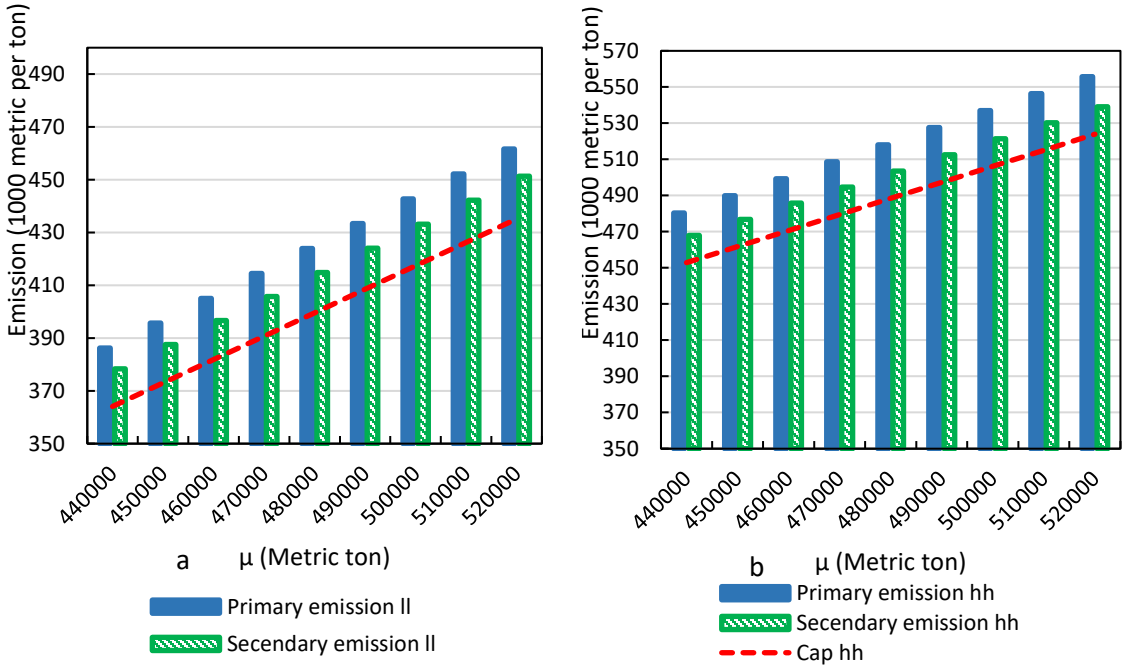

Figure 4.3. Impact of μ on emitted GHG before and after the subsidy program by the government.

According to Figure 4.4. (b), the local government's subsidy program assists the low- and high- demand pulp and paper mills reduce their GHG emissions by 2.03% and 2.60%, respectively. Increasing the average demand increases the percentage of reduced emissions. In other words, for high amounts of the average demand, the local government subsidy plan still helps the mills to reduce their emission effectively. Note that the higher the average demand is, the higher the emitted emissions are. The government subsidy contract reduces emissions for the high pulp and paper mill type more than the low-demand factory. A question that may arise is whether the amount of reduced emissions relates only to the pulp and paper investment level or whether the local government's subsidy also plays a role.

To explore the role of the local government in the technology investment of the pulp and paper mill, I illustrate my findings in Figure 4.5. It shows the government's average investment share through the subsidy contract and low-and-high types of pulp and paper mills in Figures 4.5 (a) and (b), respectively. Please note that the average falls within the same range as the average government demand estimation of the prior figures. According to Figure 4.5 (a), the local government's average share of technology investment for low-demand mills is 57%, while the mill's part is 43%. Based on Figure 4.5 (b), the local government supports an average of 67% of the technological investment for the high-demand mill, while the mill spends 33%. The local government supports the high-demand pulp and paper plant by about 10% more than the low-type. Although the high-emitting mill should invest more than the

low-emitting type, the subsidy scheme helps her cut GHG emissions more than the low-emitting one. Again, this demonstrates that the local government more supports high-demand mills than low-demand mills.

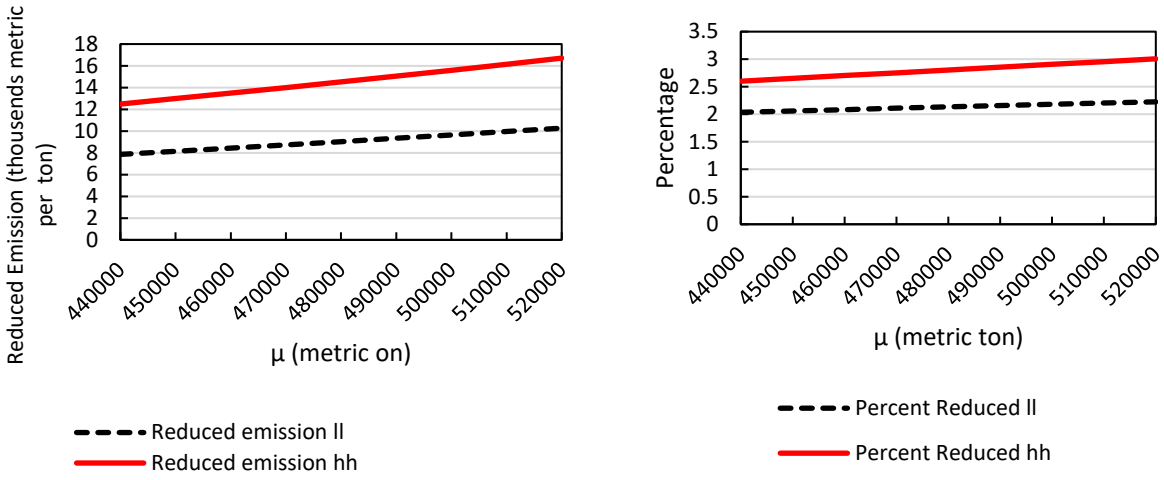

Figure 4.4. Impact of μ on the amount and the percentage of reduced emission.

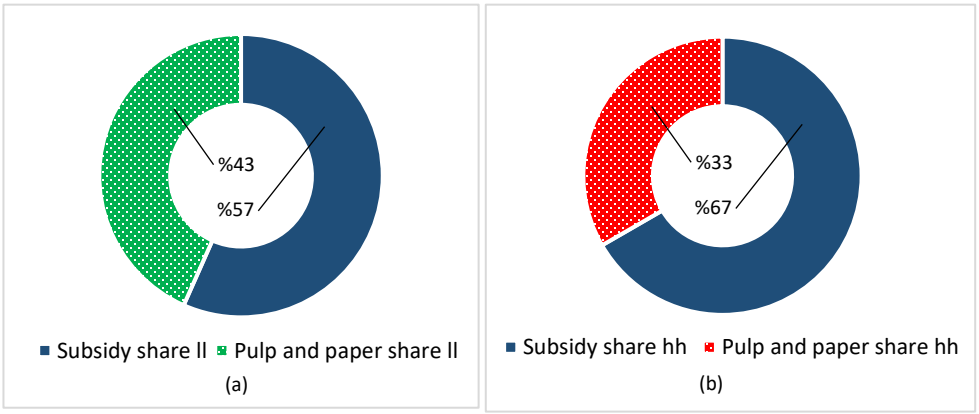

Figure 4.5. Average of investment share for the government and pulp and paper mills.

4.2. Impacts of uncertainty level of estimation

This section explores the effect of the local government's estimation of the demand uncertainty, σ^2, on SBSC players' decision variables, profits, and sustainability

indicators. Please note that the average demand is fixed in these analyses. Notably, the greater the uncertainty level, the less accurate the government estimates the demand. In other words, as estimation uncertainty increases, the government's assessment of its demand is more significant for high-demand and less sizable for low-demand. Figure 4.6. shows the effect of the uncertainty level of estimation on SBSC's decision variables. The impact of estimation uncertainty on the government's subsidy plan, T_l and T_h is shown in Figure 4.6. (a). According to the results of the model solving, the subsidy mechanisms S_l and S_h are both zero, thus, they are not included. Figure 4.6. (b) depicts the impact of σ^2 on the pulp and paper mill's decision variables, I_{ll} and I_{hh}. The subsidy contract ensures that the pulp and paper mill is honest. Thus, only the investment levels of truth-telling scenarios, I_{ll} and l_{hh}, are investigated here.

Figure 4.6 (a) shows that by increasing the estimation uncertainty level, the transfer payment subsidy for the high-demand pulp and paper mill does not change while it raises for the low-demand mill. According to figure 4.6 (b), technology investment in high-demand pulp and paper plants would rise despite constant transfer subsidies as the local government's assessment uncertainty level increases. Low-demand mill decreases her level of technology investment as the estimate uncertainty level grows. The growth and decrease in the investment in high- and low-demand mills are because of the local government's overestimated and underestimated demands as the estimation uncertainty level increases. However, one might wonder why the government raises the transfer subsidy when he is aware that by raising the estimation's level of uncertainty, the demand for low-demand mills declines. To find

the answer to this query, Figure 4.7 examines the profit the SBSC parties will make under the subsidy contract considering various amounts of the local government's estimation of the demand uncertainty. This Figure shows that each SBSC party would make either a positive or zero profit, which meets my goal. The high-demand profit is growing, although her subsidy is constant, and she is investing more in technology to decrease GHG emissions. The government keeps the low-demand mill from being forced into bankruptcy by offering an appropriate subsidy contract, despite his profit not significantly increasing. Accordingly, the local government is supporting the low-demand mill at a higher rate than expected.

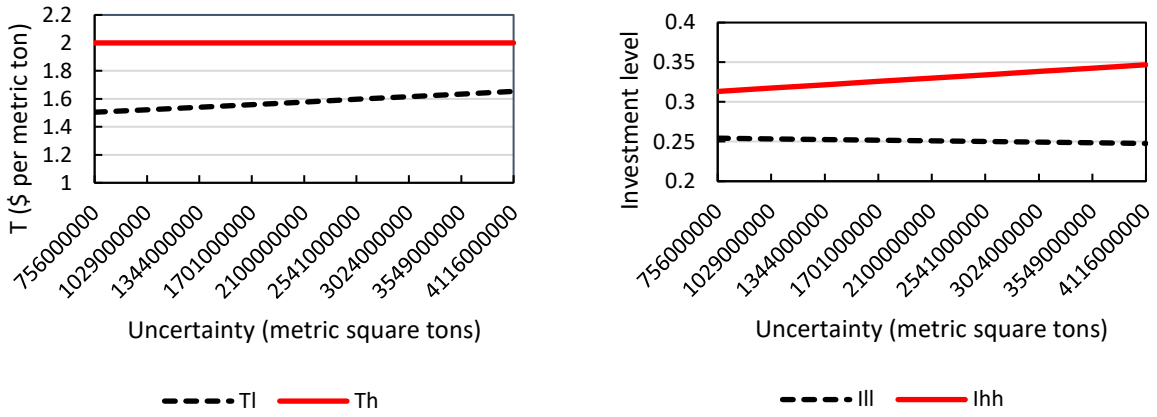

Figure 4.6. Impact of uncertainty level σ^2 on subsidy T_j and investment level I_{ij}.

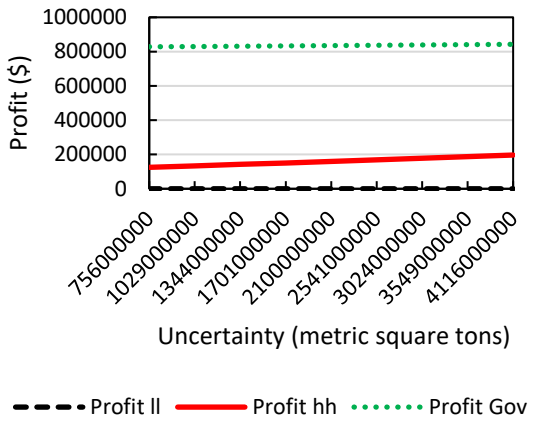

Figure 4.7. Impact of uncertainty level σ^2 on profits of each supply chain player.

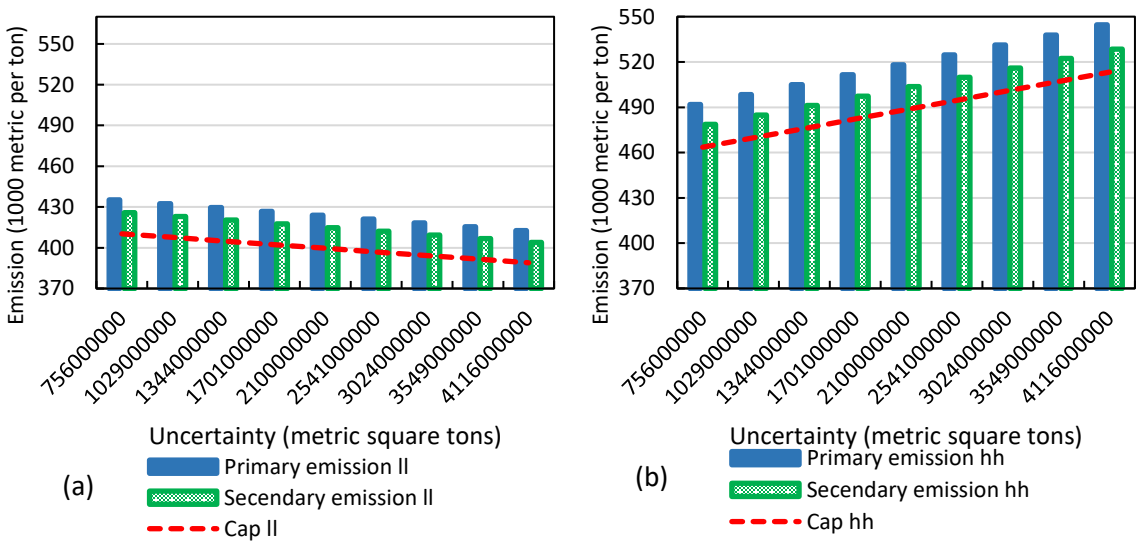

Figure 4.8. Impact of uncertainty level σ^2 on emitted GHG before and after subsidy programs by the government.

Figures 4.8, 4.9, and 4.10 evaluate the efficacy of the proposed subsidy plan concerning the SBSC's sustainability in the context of the cap-and-trade regulatory framework. Figure 4.3 (a) and (b) represent the effect of the subsidy program on GHG emissions before and after subsidy and cap-and-trade for low-demand and high-

demand types of pulp and paper mills, respectively. You can find the definitions of primary emission, secondary emission, and the amount of reduced emission in Equations 4.3, 4.4, and 4.5, respectively. According to Figure 4.8, both pulp and paper mills reduce GHG emissions under the subsidy program. However, the secondary emitted GHGs are still over the maximum permissible GHG levels, which are shown as Cap ll and Cap hh in Figure 4.8 (a) and (b), respectively. Taking the examples of the first and last points in Figure 4.3. (a), the primary and secondary emissions of the low-demand mill are 435,204 and 425,804, while the cap is 410,256 for the minimum point of uncertainty level of estimation. Moreover, the primary and secondary emissions of the high-demand mill are 491,724 and 478,644, while the cap is 463,536 in Figure 4.3. (b) for the minimum point of uncertainty level of estimation.

Figure 4.9 depicts the exact amount (a) and percentage (b) of reduced emissions due to the local government's implementation of the subsidy program so that the difference can be understood with better transparency. Figure 4.9 (a) indicates that at the minimum point of uncertainty level of estimation, the reduced GHG emissions for mills with low-demand and those with high-demand are 9,399 and 13,079, respectively. According to Figure 4.9 (b), the local government's subsidy program helps the low-and- high types of pulp and paper mills reduce their GHG emissions by 2.16% and 2.66%, respectively. By growing the uncertainty level of estimation, the reduced percentage of emission increases for the high-demand mill and decreases for the low-demand mill. The higher the estimation uncertainty, the higher the emissions for the mill with high-demand and the lower the emissions for the mill with low-demand. Therefore, for high estimation uncertainty, the local government subsidy

plan still helps the mills reduce their emission effectively. In addition, the local government subsidy contract results in a more significant reduction in emissions for the high-type pulp and paper mill than for the low-type.

Figure 4.10 illustrates the role of the local government in the technology investment of pulp and paper mills. It shows the average investment share of the local government through the subsidy contract along with low-and-high demand types of pulp and paper mills in Figures 4.10 (a) and (b), respectively. Please remember that the average falls within the same range as the amounts of estimation uncertainty in the previous figures. Based on Figure 4.10 (a), the local government supports an average of 67% of the technology investment of the low-demand mill, while the mill spends 33% on GHG emission expenditures. Based on Figure 4.10 (b), the local government's average share of technology investment for the high-demand type of mill is 67%, while the mill's part is 33%. The government subsidizes the high-demand pulp and paper mill approximately 10 percent more than the low-demand mill. Although the high-emitting kind of mill should invest more than the low-emitting type, the subsidy program helps her reduce GHG emissions more than the low-emitting one (see Figure 4.9 (b)). Overall, this indicates that the local government is more supportive of the mill with high-demand than the mill with low-demand.

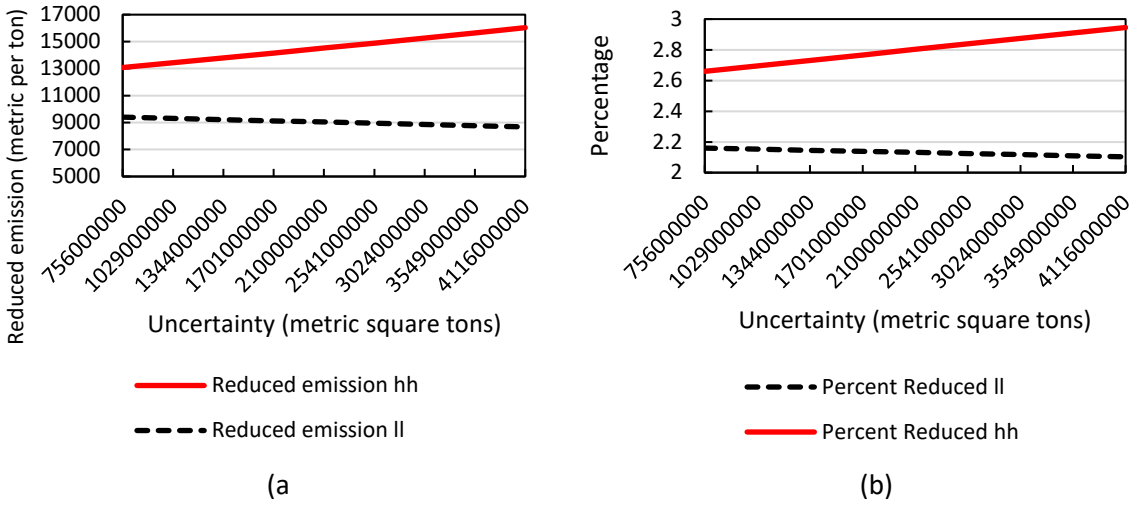

Figure 4.9. Impact of uncertainty level σ^2 on amount and percent of reduced emission.

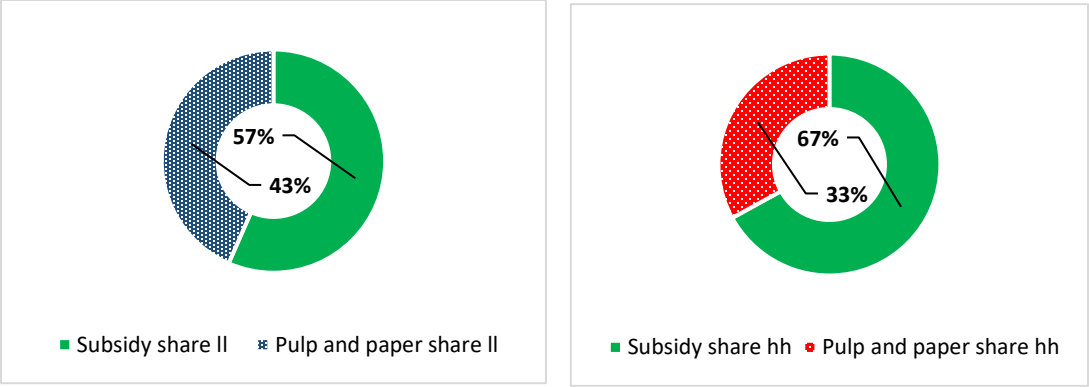

Figure 4.10. Average of investment share for the government and pulp and paper.

4.3. Impact of the carbon price on SBSC sustainability

This subsection is provided to evaluate the impact of the government's cap-and-trade mechanism on SBSC's sustainability level. Adopting the previous subsections' numerical examples along with $d_l = 650{,}000$ and $d_h = 800{,}000$, I numerically analyze the effect of carbon price α on the studied SBSC decisions, profits, and

sustainability measurements. As the goal is to move towards a more sustainable supply chain, the increase in the carbon price compared to the current value is analyzed, and the range is $50 to $60 per metric ton. I will explore whether an increased carbon price may result in a more sustainable pulp and paper industry. Figures 4.11 (a) and (b) depict the effect of the carbon price on SBSC decision variables, subsidy, and technology investment level, respectively. According to Figure 4.11 (a), the local government's subsidy for the low-demand pulp and paper mill is increasing by enhancing the carbon price while decreasing the high-demand mill. It means the government would support the low-demand mill more than the high-demand mill. However, both types of pulp and paper mills would increase their investment level in technology improvement. See figure 4.11 (b). Increasing the carbon price incur more cost for the high-demand mill. As shown in Figure 4.12, the profit of the high-demand mill is decreasing, while the government protects the low-demand mill from bankruptcy, and the local government would make a higher profit by raising the carbon price.

Figure 4.13 summarizes the impact of the carbon price increases on GHG emissions. As shown in Figure 4.13 (a), reducing GHG emissions is boosted by increasing the carbon price. Generally, the high-demand mill's GHG reduction is more than the low-demand mill. According to Figure 4.13 (b), the percent of reduced GHG emissions for the high and low-demand mills for carbon price 50 is 4.07% and 2.56%, and for carbon price 60 are 4.3% and 3.4%, respectively. Comparing these two points for high- and low-demand mills shows that the low-demand mill would reduce more GHG emissions for higher carbon prices.

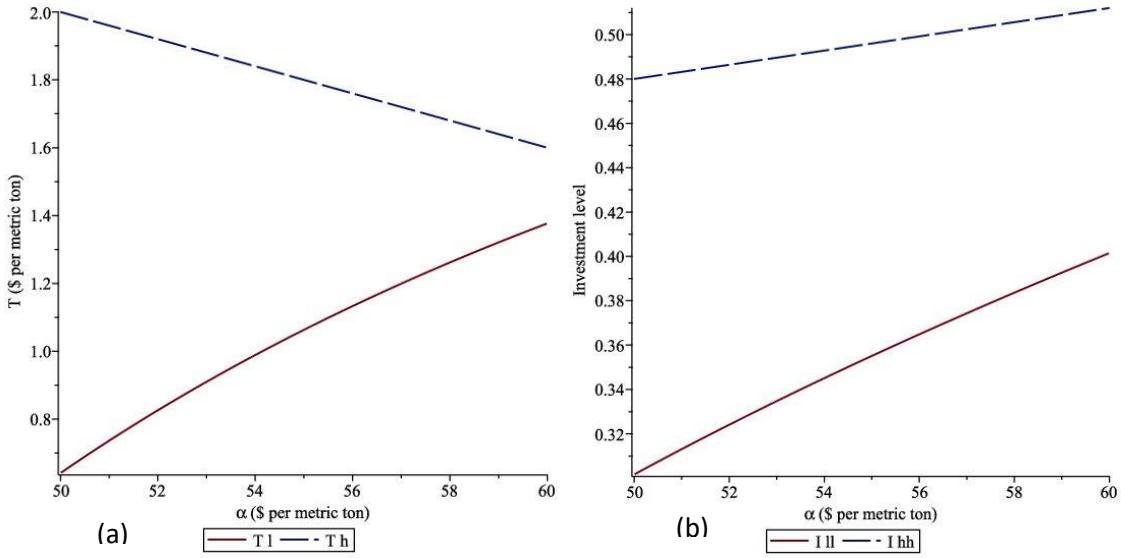

Figure 4.11. Impact of carbon price α on subsidy T_j and investment level I_{ij}.

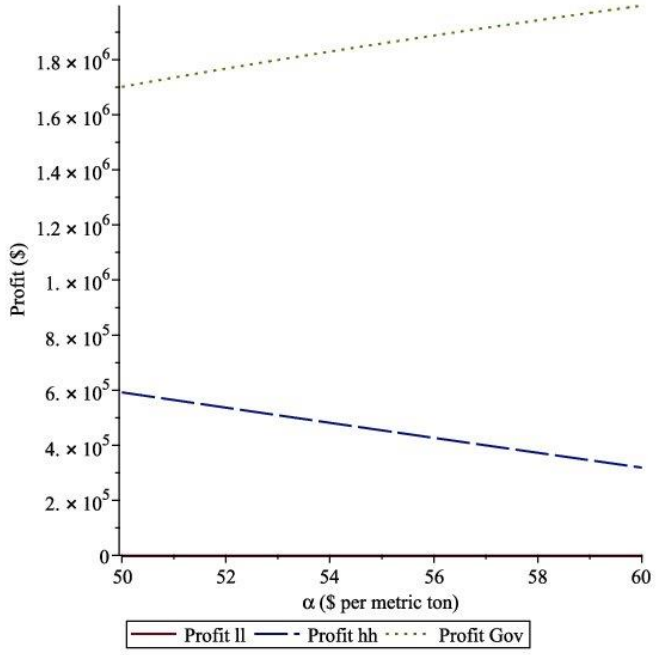

Figure 4.12. Impact of carbon price α on profits of each supply chain player.

In other words, increasing the carbon price to induce the mills to decrease the GHG emissions works, and it would result in more GHG reduction for the low-demand type. However, the high-demand mill is the only party of the studied SBSC that suffers from

increasing the carbon price. All in all, boosting the carbon price would be an environmentally friendly decision made by the local government under a favorable subsidy contract that considers all SBCS participants' viewpoints.

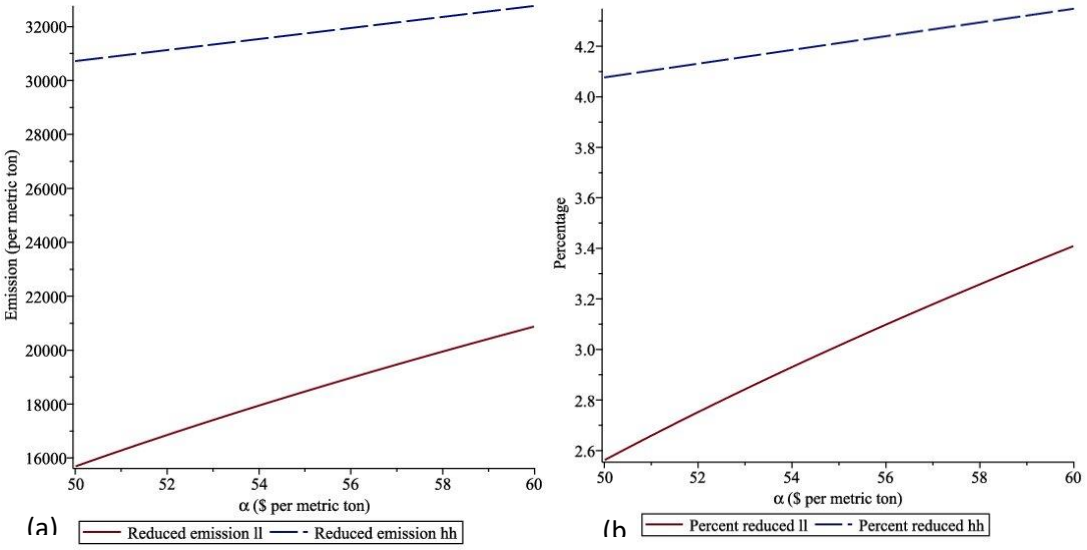

Figure 4.13. Impact of carbon price α ($) on amount (metric per ton) and percent of reduced emission.

Chapter 5. Conclusions

In the first phase of my thesis, I conduct a systematic literature review on SBSC applications. I apply the four-step content analysis methodology: material collection, descriptive analysis, categorization, and material analysis. The descriptive analysis of the previous studies identifies the leading journals contributing the most quantitative papers on SBSCs and reveals the research trends in this context. The review results are comprehensively analyzed from three main viewpoints: biomass supply chain management, sustainability dimensions, and modeling approach.

In the quantitative analysis phase of my thesis, according to the literature gaps and needs of the Canadian biomass supply chain sector, I studied an uncertainty problem in the pulp and paper sector. The studied SBSC includes two decision-makers, a pulp and paper mill, and the local government. The government actively takes sustainability issues and tactics into consideration. To progress towards sustainable improvement, the government implements a cap-and-trade system by establishing an emission allowance of GHG generated by the pulp and paper, which permits extra emissions to be acquired from other enterprises that have not emitted their acceptable amount entirely. The pulp and paper mill should put money into improving technology to cut down on the amount of GHG emissions. This technological advancement incurs expenditures for the pulp and paper mill, influencing its decision on the amount of technological advancement. In such a scenario, the local government offers a subsidy program to encourage the pulp and paper mill to increase investment and decrease GHG emissions.

The pulp and paper mill's demand pattern is private information, and the local government uses his observations in the past to estimate whether the mill's demand is low or high. An increase in pulp and paper demand leads to a rise in carbon emissions, necessitating a more significant investment in technological development to lower the mill's carbon trading costs under the cap-and-trade system. In such a situation, the government provides a subsidy program and transfer payment utilizing a principal-agent contract based on asymmetric demand information to encourage the pulp and paper industry to increase its green expenditures, reducing environmental impacts. Meanwhile, the local government must verify that the mill is telling the truth about demand, and the only way to do so is to provide an enticing subsidy deal. The decision variables (including the technology investment levels and subsidies that result from the Lagrange model to solve the original problem) are provided in section 3.

The model is numerically analyzed under different demand averages, estimation uncertainties, and carbon prices. For different amounts of the average estimated demand, the principal-agent contract with the pulp and paper mill allows the local government to choose an appropriate subsidy scheme and even prevent the mill from bankruptcy. Furthermore, even if her subsidy is constant, the high-demand profit is growing, and she is spending more on technology to reduce GHG emissions. Under the subsidy scheme, high-demand and low-demand pulp and paper mills lower GHG emissions by boosting average estimating demand, while secondary released GHGs remain over the maximum permitted GHG levels. Given large quantities of average estimated demand, the local government subsidy scheme still efficiently assists mills

in reducing emissions. Overall, the government subsidy contract reduces emissions more for high-demand pulp and paper mills than for low-demand mills.

Moreover, the local government's average technology investment share is more than both types of mill's share, but he supports the high-demand pulp and paper plant more than the low-demand type. Even though the high-emitting mill should invest more than the low-emitting type, the subsidy program would help her cut GHG emissions more than the low-emitting type. This result demonstrates that the local government more supports high-demand mills than low-demand ones.

Analyzing the effect of different uncertainty levels shows that despite constant transfer subsidies, technology investment in high-demand pulp and paper plants would rise as the local government's assessment uncertainty level rises. Although the low-demand mill is gaining more incentives, she declines the level of technology investment as the uncertainty level of estimation grows. The government raises the transfer subsidy when he is aware that increasing the estimation's level of uncertainty decreases the demand for low-demand mills. In such a case, the local government prevents the low-demand mill from bankruptcy, and he is still benefiting from the subsidy contract. Moreover, the high-demand profit is growing, although her transfer subsidy is fixed, and she is investing more in technology improvement to reduce GHG emissions.

The results of sustainability measurements of the SBCS show that even for the high levels of estimation uncertainty, both types of mills diminish GHG emissions under the subsidy contract. Additionally, compared to the low-type mill, the high-type

factory has a more considerable decrease in emissions. The government provides around 10% more assistance to the high-demand pulp and paper mill than the low-demand mill. The subsidy contract helps the high-emitting mill cut GHG emissions more than the low-emitting mill, even though the high-emitting mill must spend more money than the low-emitting mill. This finding suggests that the local government favors the high-demand mill more than the low-demand mill. It is concluded that the government supports both firms, but for the high-demand mill, the support results in more sustainable actions, while the low-demand results in preventing economic crisis.

Analyzing the carbon price changes show that the local government subsidy for low-demand pulp and paper mills increases when the carbon price rises, whereas it decreases for high-demand mills, which indicates that the government would assist the mill with low-demand more than the mill with high demand. Both types of pulp and paper mills would increase their investment in technological development. Increasing the price of carbon seems to incur additional expenses for high-demand mills. The reduced GHG emissions for both mills are boosted by increasing the carbon price. Generally, the high-demand mill reduces GHG emissions more than the low-demand mill. However, in contrast to the high-demand mill, the low-demand mill would cut GHG emissions more when carbon prices are higher. In other words, raising the carbon price to push mills to reduce GHG emissions is effective, and it would lead to a more significant reduction in GHG emissions for low-demand pulp and paper mills. However, only the high-demand mill in the analyzed SBSC suffers from an increased carbon price. Overall, the local government's choice to increase the carbon

price under a favorable subsidy contract that takes into consideration the opinions of all SBCS members would be an environmentally friendly decision.

5.1. Future research extensions

Considering a more general distribution function for demand prediction by the government rather than only two space outcomes could be one of my model extensions. I suggest future studies investigate stochastic demand patterns from the supply chain perspective. Moreover, studying the existence of multiple supply chains in the game to allow allowance sales in a secondary market is recommended.

To extend my literature review, I suggest a comprehensive bibliographic study to identify the influential authors, leading universities, and countries contributing to SBSCs. Additionally, citation and co-citation analysis through a network analysis would discover influential papers published on this topic. The work of Fahimnia et al. (2015) provides a detailed explanation of bibliometric and network analysis. Last but not least, future studies could analyze SBSC applications focusing on specific research areas, such as biomass feedstock inputs and outputs, specific quantification models, uncertainty and risk, and governmental regulations.

Chapter 6. Appendix

Table 6.1. Investigated government policies.

Government Sustainability Regulations	References
Government incentive	(Haji Esmaeili et al., 2020), (Chaharsooghi & Kashan, 2020), (Rivera-Cadavid et al., 2019), (Mohamed Abdul Ghani et al., 2020), (Yılmaz Balaman et al., 2019), (N. Zhao & You, 2019), (Aslaam et al., 2018), (Bruckman et al., 2018), (Yazan, Fraccascia, et al., 2018), (Wen & Zhou, 2018), (Wolde et al., 2017), (Cobuloglu & Büyüktahtakin, 2015), (Lam et al., 2013), (Yang et al., 2020)
Government subsidy	(F. Ye, et al., 2020b), (Yang et al., 2020), (Ye, Cai, et al., 2020), (Yun et al., 2020), (Naeini et al., 2020), (Fan et al., 2019a), (Moncada et al., 2019), (Kuo et al., 2019), (Bajgiran et al., 2019), (Calderón & Papageorgiou, 2018), (Benali et al., 2018), (Tan et al., 2017), (F. Ye, et al., 2020a), (Wang et al., 2017), (Yong Zhang & Jiang, 2017), (Azadeh & Vafa Arani, 2016), (Inghels et al., 2016), (Eker & Daalen, 2015), (Touš et al., 2011), (Rentizelas et al., 2009), (Pakravan, 2020), (Ye, Cai, et al., 2020)
Government tax	(Malladi & Sowlati, 2020), (Gilani & Sahebi, 2020), (Saghaei & Dehghanimadvar, 2020), (Yun et al., 2020), (Dioha & Kumar, 2020), (Ahmed & Sarkar, 2019), (Han & Kim, 2019), (Alizadeh et al., 2019), (Moncada et al., 2019), (Park et al., 2019), (Gas et al., 2019), (Gonela, 2018), (Mutenure et al., 2018), (Memari et al., 2018), (Sánchez-Bautista et al., 2017), (Hernández-Calderón et al., 2016), (Song et al., 2015), (Marufuzzaman et al., 2014), (Palak et al., 2014), (Giarola et al., 2020), (Osmani & Zhang, 2013), (Akgul et al., 2012), (Giarola, Zamboni, et al., 2012), (Iliopoulos & Rozakis, 2010)
Government regulation	(Dharmawan et al., 2020), (Kittler et al., 2020), (Allameh et al., 2019), (Buliga & Nichiforel, 2019), (Cantegril et al., 2019), (Palander et al., 2018), (Smith et al., 2018), (Chávez et al., 2018), (Trujillo-Mata et al., 2018), (Palander et al., 2018), (Vaccaro et al., 2018), (Jeong & Ramírez-Gómez, 2018), (Memari et al., 2018), (Hombach et al., 2016), (Azadeh & Vafa Arani, 2016), (Y. Bai et al., 2016), (Mazzetto et al., 2015), (Santibañez-Aguilar et al., 2013), (Giarola, Shah, et al., 2012), (Touš et al., 2011), (Howard et al., 2009)

Proof of Proposition 1.

To obtain both players optimal strategies, I solved the following Lagrange function in Maple 2021.

$$L(S_i, T_i) = p\left(ue_2 I_{ll} d_l - T_l I_{ll} d_l - \frac{1}{2} S_l \beta I_{ll}^2\right) + (1-p)\left(ue_2 I_{hh} d_h - T_h I_{hh} d_h - \frac{1}{2} S_h \beta I_{hh}^2\right) + \lambda_1 M_1 + \lambda_2 M_2 + \lambda_3 M_3 + \lambda_4 M_4 + \lambda_5 M_5 + \lambda_6 M_6 + \lambda_7 M_7 + \lambda_8 M_8 + \lambda_9 M_9 + \lambda_{10} M_{10}$$

Where M_K is as follows:

$$M_1 = (r + T_l I_{ll} - c) d_l - \alpha\big((e_1 - e_2 I_{ll}) d_l - e_3 d_l\big) - (1 - S_l)\left(\frac{1}{2}\beta I_{ll}^2\right) - f_1^2$$

$$M_2 = (r + T_h I_{hh} - c) d_h - \alpha\big((e_1 - e_2 I_{hh}) d_h - e_3 d_h\big) - (1 - S_h)\left(\frac{1}{2}\beta I_{hh}^2\right) - f_2^2$$

$$M_3 = (r + T_l I_{ll} - c) d_l - \alpha\big((e_1 - e_2 I_{ll}) d_l - e_3 d_l\big) - (1 - S_l)\left(\frac{1}{2}\beta I_{ll}^2\right) - (r + T_h I_{lh} - c) d_l - \alpha\big((e_1 - e_2 I_{lh}) d_l - e_3 d_l\big) - (1 - S_h)\left(\frac{1}{2}\beta I_{lh}^2\right) - f_3^2$$

$$M_4 = (r + T_h I_{hh} - c) d_h - \alpha\big((e_1 - e_2 I_{hh}) d_h - e_3 d_h\big) - (1 - S_h)\left(\frac{1}{2}\beta I_{hh}^2\right) - (r + T_l I_{hl} - c) d_h - \alpha\big((e_1 - e_2 I_{hl}) d_h - e_3 d_h\big) - (1 - S_l)\left(\frac{1}{2}\beta I_{hl}^2\right) - f_4^2$$

$M_5 = S_l - 1 + f_5^2, M_6 = S_l - f_6^2, M_7 = S_h - 1 + f_7^2, M_8 = S_h - f_8^2.$

$\lambda_k M_k = 0, M_k \geq 0, \lambda_k \geq 0, k = 1, \ldots, 8$

I got two solutions for the problem's decision variables. Please note that all parameters are positive and $p\epsilon(0,1), d_h > d_l, r > c, e_1 > e_3$.

The details of the first solution are as follows:

$$\lambda_1 = p\left(\frac{e_2 d_l(\alpha+u) + 2\sqrt{2\beta d_l(\alpha(e_1-e_3)+c-r)}}{\sqrt{2\beta d_l(\alpha(e_1-e_3)+c-r)}}\right),\ \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_7 = 0,$$

$\lambda_6 = \frac{0.5pd_l(e_2(\alpha+u)\sqrt{2\beta d_l(\alpha(e_1-e_3)+c-r)}-2\beta(\alpha(e_1-e_3)+c-r))}{\beta}$, $\lambda_8 = \frac{0.125e_2^2 d_h^2(1-p)(a+u)^2}{\beta}$.

From $\lambda_1 \geq 0$ I have $\alpha(e_1 - e_3) + c - r \geq 0$, λ_8 is always positive, and from $\lambda_6 \geq 0$, I have $\alpha(e_1 - e_3) + c - r$ and $d_l \geq \frac{\sqrt{2\beta d_l(\alpha(e_1-e_3)+c-r)}}{e_2(\alpha+u)}$.

Therefore, final constraints are $\alpha(e_1 - e_3) + c - r \geq 0$ and $d_l \geq \frac{\sqrt{2\beta d_l(\alpha(e_1-e_3)+c-r)}}{e_2(\alpha+u)}$

The first solution of the local government's subsidies are:

$S_l = 0$

$S_h = 0$

$T_l = \frac{-\alpha e_2 d_l + \sqrt{2\beta d_l(\alpha(e_1 - e_3) + c - r)}}{d_l}$

$T_h = 0.5e_2(u - \alpha)$

Proof of Proposition 2.

The second solution is as follows:

$\lambda_2 = \frac{(p-1)(-e_2 d_h(\alpha+u)+2\sqrt{2\beta d_h(\alpha(e_1-e_3)+c-r)})}{\sqrt{2\beta d_h(\alpha(e_1-e_3)+c-r)}}$, $\lambda_1 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_7 = 0$,

$\lambda_6 = \frac{0.125pe_2^2 d_l^2(a+u)^2}{\beta}$, $\lambda_8 = \frac{-0.5d_h(1-p)(-e_2(\alpha+u)\sqrt{2\beta d_h(\alpha(e_1-e_3)+c-r)}+2\beta(\alpha(e_1-e_3)+c-r))}{\beta}$.

From $\lambda_2 \geq 0$, I have $\alpha(e_1 - e_3) + c - r \geq 0$ and $d_h \geq \frac{2\sqrt{2\beta d_h(\alpha(e_1-e_3)+c-r)}}{e_2(\alpha+u)}$, λ_6 is always positive, and from $\lambda_8 \geq 0$, I have: $\alpha(e_1 - e_3) + c - r \geq 0$ and $d_h \geq \frac{\sqrt{2\beta d_h(\alpha(e_1-e_3)+c-r)}}{e_2(\alpha+u)}$.

Therefore, final constraints are: $\alpha(e_1 - e_3) + c - r \geq 0, d_h \geq \frac{2\sqrt{2\beta d_h(\alpha(e_1-e_3)+c-r)}}{e_2(\alpha+u)}$

The second solution is:

$S_l = 0$

$S_h = 0$

$T_l = 0.5e_2(u - \alpha)$

$T_h = \frac{-\alpha e_2 d_h + \sqrt{2\beta d_h(\alpha(e_1-e_3)+c-r)}}{d_h}$

References

Aboytes-Ojeda, M., Castillo-Villar, K. K., & Roni, M. S. (2020). A decomposition approach based on meta-heuristics and exact methods for solving a two-stage stochastic biofuel hub-and-spoke network problem. *Journal of Cleaner Production*, *247*, 119176. https://doi.org/10.1016/j.jclepro.2019.119176

Abriyantoro, D., Dong, J., Hicks, C., & Singh, S. P. (2019). A stochastic optimisation model for biomass outsourcing in the cement manufacturing industry with production planning constraints. *Energy*, *169*, 515–526. https://doi.org/10.1016/j.energy.2018.11.114

Ahmed, W., & Sarkar, B. (2018). Impact of carbon emissions in a sustainable supply chain management for a second generation biofuel. *Journal of Cleaner Production*, *186*, 807–820. https://doi.org/10.1016/j.jclepro.2018.02.289

Ahmed, W., & Sarkar, B. (2019). Resources , Conservation & Recycling Management of next-generation energy using a triple bottom line approach under a supply chain framework. *Resources, Conservation & Recycling*, *150*(August), 104431. https://doi.org/10.1016/j.resconrec.2019.104431

Akbarian-Saravi, N., Mobini, M., & Rabbani, M. (2020). Development of a comprehensive decision support tool for strategic and tactical planning of a sustainable bioethanol supply chain: Real case study, discussions and policy implications. *Journal of Cleaner Production*, *244*, 118871. https://doi.org/10.1016/j.jclepro.2019.118871

Akgul, O., Shah, N., & Papageorgiou, L. G. (2012). An optimisation framework for a hybrid first/second generation bioethanol supply chain. *Computers and Chemical Engineering*, *42*, 101–114. https://doi.org/10.1016/j.compchemeng.2012.01.012

Alaoui, M. El. (2020). Fuzzy goal programming for biodiesel production. *International Journal of Green Energy*, *17*(11), 644–651. https://doi.org/10.1080/15435075.2020.1779075

Alizadeh, M., Ma, J., Marufuzzaman, M., & Yu, F. (2019). Sustainable ole fi n supply chain network design under seasonal feedstock supplies and uncertain carbon tax rate. *Journal of Cleaner Production*, *222*, 280–299. https://doi.org/10.1016/j.jclepro.2019.02.188

Allameh, G., Mehrabad, M. S., & Sadjadi, S. J. (2019). Pricing decisions in a decentralized biofuel supply chain with RIN mechanism. *Energy Sources, Part B: Economics, Planning and Policy*, *14*(6), 254–273. https://doi.org/10.1080/15567249.2019.1668499

Allen, J., Browne, M., Hunter, A., Boyd, J., & Palmer, H. (1998). Logistics management and costs of biomass fuel supply. *International Journal of Physical Distribution & Logistics Management*, *28*(6), 463–477.

https://doi.org/10.1108/09600039810245120

Arabi, M., Yaghoubi, S., & Tajik, J. (2019). *Algal biofuel supply chain network design with variable demand under alternative fuel price uncertainty : A case study*. *130*. https://doi.org/10.1016/j.compchemeng.2019.106528

Asadi, E., Habibi, F., Nickel, S., & Sahebi, H. (2018). A bi-objective stochastic location-inventory-routing model for microalgae- based biofuel supply chain. *Applied Energy*, *228*(June), 2235–2261. https://doi.org/10.1016/j.apenergy.2018.07.067

Asia, S. (2020). *Operational Management Implemented in Biofuel Upstream Supply Chain and Downstream International Trading : Current Issues in*.

Aslaam, N. M., Abdul, M., & Szmerekovsky, J. (2018). *Biomass feedstock supply chain network design with biomass conversion incentives*. *116*(December 2017), 39–49. https://doi.org/10.1016/j.enpol.2018.01.042

Aviso, K. B., Tan, R. R., Culaba, A. B., & Cruz, J. B. (2011). Fuzzy input-output model for optimizing eco-industrial supply chains under water footprint constraints. *Journal of Cleaner Production*, *19*(2–3), 187–196. https://doi.org/10.1016/j.jclepro.2010.09.003

Axelsson, L., Franzén, M., Ostwald, M., Berndes, G., Lakshmi, G., & Ravindranath, N. H. (2012). Perspective: Jatropha cultivation in southern India: Assessing farmers' experiences. *Biofuels, Bioproducts and Biorefining*, *6*(3), 246–256. https://doi.org/10.1002/bbb

Ayoub, N., Elmoshi, E., Seki, H., & Naka, Y. (2009). Evolutionary algorithms approach for integrated bioenergy supply chains optimization. *Energy Conversion and Management*, *50*(12), 2944–2955. https://doi.org/10.1016/j.enconman.2009.07.010

Azadeh, A., & Vafa Arani, H. (2016). Biodiesel supply chain optimization via a hybrid system dynamics-mathematical programming approach. *Renewable Energy*, *93*, 383–403. https://doi.org/10.1016/j.renene.2016.02.070

Babazadeh, R., Razmi, J., Saman, M., & Rabbani, M. (2017). A sustainable second-generation biodiesel supply chain network design problem under risk. *Omega*, *66*, 258–277. https://doi.org/10.1016/j.omega.2015.12.010

Bai, Q., Chen, M., & Xu, L. (2017). Revenue and promotional cost-sharing contract versus two-part tariff contract in coordinating sustainable supply chain systems with deteriorating items. *International Journal of Production Economics*, *187*(January), 85–101. https://doi.org/10.1016/j.ijpe.2017.02.012

Bai, Y., Ouyang, Y., & Pang, J. S. (2016). Enhanced models and improved solution for competitive biofuel supply chain design under land use constraints. *European Journal of Operational Research*, *249*(1), 281–297. https://doi.org/10.1016/j.ejor.2015.08.027

Bais-Moleman, A. L., Sikkema, R., Vis, M., Reumerman, P., Theurl, M. C., & Erb, K. H. (2018). Assessing wood use efficiency and greenhouse gas emissions of wood product cascading in the European Union. *Journal of Cleaner Production*, *172*, 3942–3954. https://doi.org/10.1016/j.jclepro.2017.04.153

Bajgiran, A. H., Jang, J., Fang, X., & Peoples, J. H. (2019). A biofuel supply chain equilibrium analysis with subsidy consideration. *International Journal of Energy Research*, *43*(5), 1848–1867. https://doi.org/10.1002/er.4422

Barbosa-póvoa, A. P., Silva, C., & Carvalho, A. (2018). *Opportunities and challenges in sustainable supply chain : An operations research perspective*. *268*, 399–431. https://doi.org/10.1016/j.ejor.2017.10.036

Benali, M., Jeaidi, J., Mansoornejad, B., Ajao, O., Gilani, B., & Mehr, N. G. (2018). *Decision Support Systems for Assessment of Biore fi nery Transformation Strategies*. *96*(July), 2155–2175. https://doi.org/10.1002/cjce.23301

Benjamin, M. F. D. (2018). Multi-disruption criticality analysis in bioenergy-based eco-industrial parks via the P-graph approach. *Journal of Cleaner Production*, *186*, 325–334. https://doi.org/10.1016/j.jclepro.2018.03.130

Bijarchiyan, M., Sahebi, H., & Mirzamohammadi, S. (2020). *A sustainable biomass network design model for bioenergy production by anaerobic digestion technology : using agricultural residues and livestock manure*. *7*, 1–18.

Boldrin, A., Baral, K. R., Fitamo, T., Vazifehkhoran, A. H., Jensen, I. G., Kjærgaard, I., Lyng, K. A., van Nguyen, Q., Nielsen, L. S., & Triolo, J. M. (2016). Optimised biogas production from the co-digestion of sugar beet with pig slurry: Integrating energy, GHG and economic accounting. *Energy*, *112*(2016), 606–617. https://doi.org/10.1016/j.energy.2016.06.068

Brandenburg, M., Govindan, K., Sarkis, J., & Seuring, S. (2014). Quantitative models for sustainable supply chain management : Developments and directions. *European Journal of Operational Research*, *233*(2), 299–312. https://doi.org/10.1016/j.ejor.2013.09.032

Bruckman, V. J., Haruthaithanasan, M., Miller, R. O., Terada, T., Brenner, A., Kraxner, F., & Flaspohler, D. (2018). *Sustainable Forest Bioenergy Development Strategies in Indochina : Collaborative Effort to Establish Regional Policies*. *v*, 1–21. https://doi.org/10.3390/f9040223

Budzianowski, W. M., & Postawa, K. (2016). Total Chain Integration of sustainable biorefinery systems. *Applied Energy*, *184*, 1432–1446. https://doi.org/10.1016/j.apenergy.2016.06.050

Buliga, B., & Nichiforel, L. (2019). Voluntary forest certification vs. stringent legal frameworks: Romania as a case study. *Journal of Cleaner Production*, *207*, 329–342. https://doi.org/10.1016/j.jclepro.2018.10.021

Caldeira, C., Swei, O., Freire, F., Dias, L. C., Olivetti, E. A., & Kirchain, R. (2019). Planning

strategies to address operational and price uncertainty in biodiesel production. *Applied Energy*, *238*(February 2018), 1573–1581. https://doi.org/10.1016/j.apenergy.2019.01.195

Calderón, A. J., & Papageorgiou, L. G. (2018). Biomass and Bioenergy Key aspects in the strategic development of synthetic natural gas (BioSNG) supply chains. *Biomass and Bioenergy*, *110*(June 2017), 80–97. https://doi.org/10.1016/j.biombioe.2018.01.004

Cambero, C., & Sowlati, T. (2014). Assessment and optimization of forest biomass supply chains from economic, social and environmental perspectives - A review of literature. *Renewable and Sustainable Energy Reviews*, *36*, 62–73. https://doi.org/10.1016/j.rser.2014.04.041

Cantegril, P., Paradis, G., LeBel, L., & Raulier, F. (2019). Bioenergy production to improve value-creation potential of strategic forest management plans in mixed-wood forests of Eastern Canada. *Applied Energy*, *247*(March), 171–181. https://doi.org/10.1016/j.apenergy.2019.04.022

Chaharsooghi, M. R. S. K., & Kashan, A. H. (2020). *Optimal design and planning of biodiesel supply chain network : a scenario - based robust optimization approach*. 111–128.

Chávez, M. M. M., Sarache, W., & Costa, Y. (2018). Towards a comprehensive model of a biofuel supply chain optimization from coffee crop residues. *Transportation Research Part E: Logistics and Transportation Review*, *116*(June), 136–162. https://doi.org/10.1016/j.tre.2018.06.001

Chazara, P., Negny, S., & Montastruc, L. (2017). Quantitative method to assess the number of jobs created by production systems : Application to multi-criteria decision analysis for sustainable biomass supply chain. *Sustainable Production and Consumption*, *12*(August), 134–154. https://doi.org/10.1016/j.spc.2017.07.002

Chitawo, M. L., Chimphango, A. F. A., & Peterson, S. (2018). Biomass and Bioenergy Modelling sustainability of primary forest residues-based bioenergy system. *Biomass and Bioenergy*, *108*(October 2017), 90–100. https://doi.org/10.1016/j.biombioe.2017.10.022

Cobuloglu, H. I., & Büyüktahtakin, I. E. (2015). Food vs. biofuel: An optimization approach to the spatio-temporal analysis of land-use competition and environmental impacts. *Applied Energy*, *140*, 418–434. https://doi.org/10.1016/j.apenergy.2014.11.080

De Meyer, A., Cattrysse, D., Rasinmäki, J., & Van Orshoven, J. (2014). Methods to optimise the design and management of biomass-for-bioenergy supply chains: A review. *Renewable and Sustainable Energy Reviews*, *31*, 657–670. https://doi.org/10.1016/j.rser.2013.12.036

De Meyer, A., Cattrysse, D., Snoeck, M., & Van Orshoven, J. (2012). Generic data model

to represent the biomass-to-bioenergy supply chain logistics. *International Conference on Agricultural Engineering (CIGR-Ageng2012)*, *January 2015*, C0156.

Dharmawan, A. H., Fauzi, A., Putri, E. I. K., Pacheco, P., Dermawan, A., Nuva, N., Amalia, R., & Sudaryanti, D. A. (2020). Bioenergy policy: The biodiesel sustainability dilemma in Indonesia. *International Journal of Sustainable Development and Planning*, *15*(4), 537–546. https://doi.org/10.18280/ijsdp.150414

Díaz-Trujillo, L. A., & Nápoles-Rivera, F. (2019). Optimization of biogas supply chain in Mexico considering economic and environmental aspects. *Renewable Energy*, *139*, 1227–1240. https://doi.org/10.1016/j.renene.2019.03.027

Dioha, M. O., & Kumar, A. (2020). Sustainable energy pathways for land transport in Nigeria. *Utilities Policy*, *64*(August 2019), 101034. https://doi.org/10.1016/j.jup.2020.101034

Duarte, A., Sarache, W., & Costa, Y. (2016). Biofuel supply chain design from Coffee Cut Stem under environmental analysis. *Energy*, *100*, 321–331. https://doi.org/10.1016/j.energy.2016.01.076

Eguchi, S., Kagawa, S., & Okamoto, S. (2015). Environmental and economic performance of a biodiesel plant using waste cooking oil. *Journal of Cleaner Production*, *101*(August 2010), 245–250. https://doi.org/10.1016/j.jclepro.2015.04.008

Eker, S., & Daalen, E. Van. (2015). A model-based analysis of biomethane production in the Netherlands and the effectiveness of the subsidization policy under uncertainty. *Energy Policy*, *82*, 178–196. https://doi.org/10.1016/j.enpol.2015.03.019

Ekşioğlu, S. D., Acharya, A., Leightley, L. E., & Arora, S. (2009). Analyzing the design and management of biomass-to-biorefinery supply chain. *Computers and Industrial Engineering*, *57*(4), 1342–1352. https://doi.org/10.1016/j.cie.2009.07.003

Elkington, J. (1997). Cannibals with Forks: The Triple Bottom Line of 21st Century, *Business, Capstone, Oxford.*

Elisabeth, L., Büsing, C., & Walther, G. (2018). *Robust and sustainable supply chains under market uncertainties and different risk attitudes – A case study of the German biodiesel market*. *269*, 302–312. https://doi.org/10.1016/j.ejor.2017.07.015

Fan, K., Li, X., Wang, L., & Wang, M. (2019a). Computers & Industrial Engineering Two-stage supply chain contract coordination of solid biomass fuel involving multiple suppliers. *Computers & Industrial Engineering*, *135*(January), 1167–1174. https://doi.org/10.1016/j.cie.2019.01.016

Fan, K., Li, X., Wang, L., & Wang, M. (2019b). Two-stage supply chain contract coordination of solid biomass fuel involving multiple suppliers. *Computers and*

Industrial Engineering, *135*(January), 1167–1174. https://doi.org/10.1016/j.cie.2019.01.016

Fattahi, M., & Govindan, K. (2018). A multi-stage stochastic program for the sustainable design of biofuel supply chain networks under biomass supply uncertainty and disruption risk : A real-life case study. *Transportation Research Part E*, *118*(September), 534–567. https://doi.org/10.1016/j.tre.2018.08.008

Fernández-González, J. M., Martín-Pascual, J., & Zamorano, M. (2020). Biomethane injection into natural gas network vs composting and biogas production for electricity in Spain: An analysis of key decision factors. *Sustainable Cities and Society*, *60*(April), 102242. https://doi.org/10.1016/j.scs.2020.102242

Fernandez-Lacruz, R., Eriksson, A., & Bergström, D. (2020). Simulation-based cost analysis of industrial supply of chips from logging residues and small-diameter trees. *Forests*, *11*(1), 1–22. https://doi.org/10.3390/f11010001

Finnan, J., & Styles, D. (2013). Hemp: A more sustainable annual energy crop for climate and energy policy. *Energy Policy*, *58*, 152–162. https://doi.org/10.1016/j.enpol.2013.02.046

Flores Hernández, U., Jaeger, D., & Samperio, J. I. (2020). Modeling Forest Woody Biomass Availability for Energy Use Based on Short-Term Forecasting Scenarios. *Waste and Biomass Valorization*, *11*(5), 2137–2151. https://doi.org/10.1007/s12649-018-0511-7

Forest-and-Rangelands. (2015). *No Title*. https://www.forestsandrangelands.gov/woody-biomass/benefits.shtml

Gabrielle, B., Bamière, L., Caldes, N., De Cara, S., Decocq, G., Ferchaud, F., Loyce, C., Pelzer, E., Perez, Y., Wohlfahrt, J., & Richard, G. (2014). Paving the way for sustainable bioenergy in Europe: Technological options and research avenues for large-scale biomass feedstock supply. *Renewable and Sustainable Energy Reviews*, *33*, 11–25. https://doi.org/10.1016/j.rser.2014.01.050

Galanopoulos, C., Barletta, D., & Zondervan, E. (2018). A decision support platform for a bio-based supply chain : Application to the region of Lower Saxony and Bremen (Germany). *Computers and Chemical Engineering*, *115*, 233–242. https://doi.org/10.1016/j.compchemeng.2018.03.024

Galanopoulos, C., Giuliano, A., Barletta, D., & Zondervan, E. (2020). An integrated methodology for the economic and environmental assessment of a biorefinery supply chain. *Chemical Engineering Research and Design*, *160*, 199–215. https://doi.org/10.1016/j.cherd.2020.05.016

Galvez, D., Rakotondranaivo, A., Morel, L., Camargo, M., & Fick, M. (2015). based on MILP optimization and Analytical Hierarchical Process (AHP). *Journal of Manufacturing Systems*. https://doi.org/10.1016/j.jmsy.2014.12.005

Gao, C., Qu, D., & Yang, Y. (2019). Optimal design of bioenergy supply chains

considering social benefits: A case study in Northeast China. *Processes*, *7*(7). https://doi.org/10.3390/pr7070437

Garofalo, P., Mastrorilli, M., Ventrella, D., Vonella, A. V., & Campi, P. (2020). Modelling the suitability of energy crops through a fuzzy-based system approach: The case of sugar beet in the bioethanol supply chain. *Energy*, *196*, 117160. https://doi.org/10.1016/j.energy.2020.117160

Gas, S. L., D, L. A., Tovar-facio, J., & Fabricio, N. (2019). *E ff ective Use of Carbon Pricing on Climate Change Mitigation Projects : Analysis of the Biogas Supply*.

Geng, N., Zhang, Y., & Sun, Y. (2020). Location optimization of biodiesel processing plant based on rough set and clustering algorithm - A case study in China. *Engineering Review*, *40*(3), 105–115. https://doi.org/10.30765/er.40.3.11

Ghaderi, H., Pishvaee, M. S., & Moini, A. (2016). Biomass supply chain network design: An optimization-oriented review and analysis. *Industrial Crops and Products*, *94*, 972–1000. https://doi.org/10.1016/j.indcrop.2016.09.027

Ghosh, T., & Bakshi, B. R. (2019). Designing biofuel supply chains while mitigating harmful algal blooms with treatment wetlands. *Computers and Chemical Engineering*, *126*, 113–127. https://doi.org/10.1016/j.compchemeng.2019.03.041

Giarola, S., Bezzo, F., & Shah, N. (2020). A risk management approach to the economic and environmental strategic design of ethanol supply chains. *Biomass and Bioenergy*, *58*(0), 31–51. https://doi.org/10.1016/j.biombioe.2013.08.005

Giarola, S., Shah, N., & Bezzo, F. (2012). A comprehensive approach to the design of ethanol supply chains including carbon trading effects. *Bioresource Technology*, *107*, 175–185. https://doi.org/10.1016/j.biortech.2011.11.090

Giarola, S., Zamboni, A., & Bezzo, F. (2012). Environmentally conscious capacity planning and technology selection for bioethanol supply chains. *Renewable Energy*, *43*, 61–72. https://doi.org/10.1016/j.renene.2011.12.011

Gilani, H., & Sahebi, H. (2020). *A multi-objective robust optimization model to design sustainable sugarcane-to-biofuel supply network : the case of study*.

Gital, Y., & Bilgen, B. (2020). Multi-objective optimization of sustainable biomass supply chain network design. *Applied Energy*, *272*(June), 115259. https://doi.org/10.1016/j.apenergy.2020.115259

Gonela, V. (2018). Stochastic optimization of hybrid electricity supply chain considering carbon emission schemes. *Sustainable Production and Consumption*, *14*, 136–151. https://doi.org/10.1016/j.spc.2018.02.004

Gonela, V., Zhang, J., & Osmani, A. (2022). Computers & Industrial Engineering Stochastic optimization of sustainable industrial symbiosis based hybrid generation bioethanol supply chains q. *Computers & Industrial Engineering*, *87*(2015), 40–65. https://doi.org/10.1016/j.cie.2015.04.025

Gonzalez-Salazar, M. A., Venturini, M., Poganietz, W. R., Finkenrath, M., & Leal, M. R. (2017). Combining an accelerated deployment of bioenergy and land use strategies: Review and insights for a post-conflict scenario in Colombia. *Renewable and Sustainable Energy Reviews*, *73*(October 2015), 159–177. https://doi.org/10.1016/j.rser.2017.01.082

Govindan, K., Soleimani, H., & Kannan, D. (2015). Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future. *European Journal of Operational Research*, *240*(3), 603–626. https://doi.org/10.1016/j.ejor.2014.07.012

Gumte, K. M., & Mitra, K. (2019). Bio-Supply Chain Network Design to tackle ethanol de fi ciency in India : A mathematical framework. *Journal of Cleaner Production*, *234*, 208–224. https://doi.org/10.1016/j.jclepro.2019.06.160

Guo, M., Richter, G. M., Holland, R. A., Eigenbrod, F., Taylor, G., & Shah, N. (2016). Implementing land-use and ecosystem service effects into an integrated bioenergy value chain optimisation framework. *Computers and Chemical Engineering*, *91*, 392–406. https://doi.org/10.1016/j.compchemeng.2016.02.011

Haji Esmaeili, S. A., Szmerekovsky, J., Sobhani, A., Dybing, A., & Peterson, T. O. (2020). Sustainable biomass supply chain network design with biomass switching incentives for first-generation bioethanol producers. *Energy Policy*, *138*(December 2019), 111222. https://doi.org/10.1016/j.enpol.2019.111222

Halim, A., Razik, A., Seong, C., & Elkamel, A. (2019). *Food and Bioproducts Processing A model-based approach for biomass-to- bioproducts supply Chain network planning optimization*. *8*, 293–305.

Han, S., & Kim, J. (2019). A multi-period MILP model for the investment and design planning of a national-level complex renewable energy supply system. *Renewable Energy*, *141*, 736–750. https://doi.org/10.1016/j.renene.2019.04.017

Harahap, F., Leduc, S., Mesfun, S., Khatiwada, D., Kraxner, F., & Silveira, S. (2019). Opportunities to optimize the palm oil supply chain in Sumatra, Indonesia. *Energies*, *12*(3). https://doi.org/10.3390/en12030420

Hassini, E., Surti, C., & Searcy, C. (2012). A literature review and a case study of sustainable supply chains with a focus on metrics. *International Journal of Production Economics*, *140*(1), 69–82. https://doi.org/10.1016/j.ijpe.2012.01.042

He-Lambert, L., Shylo, O., English, B. C., Eash, N. S., Zahn, J. A., & Lambert, D. M. (2019). Supply chain and logistic optimization of industrial Spent Microbial Biomass distribution as a soil amendment for field crop production. *Resources, Conservation and Recycling*, *146*(March), 218–231. https://doi.org/10.1016/j.resconrec.2019.03.028

Heavey, J. P., & Volk, T. A. (2016). *The economics of growing shrub willow as a bioenergy buffer on agricultural fi elds : A case study in the*. 776–789. https://doi.org/10.1002/bbb

Hernández-Calderón, O. M., Ponce-Ortega, J. M., Ortiz-Del-Castillo, J. R., Cervantes-Gaxiola, M. E., Milán-Carrillo, J., Serna-González, M., & Rubio-Castro, E. (2016). Optimal Design of Distributed Algae-Based Biorefineries Using CO2 Emissions from Multiple Industrial Plants. *Industrial and Engineering Chemistry Research*, *55*(8), 2345–2358. https://doi.org/10.1021/acs.iecr.5b01684

Hiloidhari, M., Baruah, D. C., Singh, A., Kataki, S., Medhi, K., Kumari, S., Ramachandra, T. V., Jenkins, B. M., & Thakur, I. S. (2017). Emerging role of Geographical Information System (GIS), Life Cycle Assessment (LCA) and spatial LCA (GIS-LCA) in sustainable bioenergy planning. *Bioresource Technology*, *242*, 218–226. https://doi.org/10.1016/j.biortech.2017.03.079

Hombach, L. E., Cambero, C., Sowlati, T., & Walther, G. (2016). Optimal design of supply chains for second generation biofuels incorporating European biofuel regulations. *Journal of Cleaner Production*, *133*, 565–575. https://doi.org/10.1016/j.jclepro.2016.05.107

Hosseinalizadeh, R., Arshadi, A., & Mahdi, M. (2019). A multi-objective and multi-period model to design a strategic development program for biodiesel fuels. *Sustainable Energy Technologies and Assessments*, *36*(December 2018), 100545. https://doi.org/10.1016/j.seta.2019.100545

Howard, D. C., Wadsworth, R. A., Whitaker, J. W., Hughes, N., & Bunce, R. G. H. (2009). The impact of sustainable energy production on land use in Britain through to 2050. *Land Use Policy*, *26*(SUPPL. 1), 284–292. https://doi.org/10.1016/j.landusepol.2009.09.017

Iliopoulos, C., & Rozakis, S. (2010). Environmental cost-effectiveness of bio diesel production in Greece : Current policies and alternative scenarios $. *Energy Policy*, *38*(2), 1067–1078. https://doi.org/10.1016/j.enpol.2009.10.059

Inghels, D., Dullaert, W., & Bloemhof, J. (2016). Resources , Conservation and Recycling A model for improving sustainable green waste recovery. *"Resources, Conservation & Recycling," 110*, 61–73. https://doi.org/10.1016/j.resconrec.2016.03.013

IRENA. (2015). *No Title*. International Renewable Energy Agency. https://www.irena.org/

IRENA. (2021). *No Title*. International Renewable Energy Agency. https://www.irena.org/

Jeong, J. S., & González-Gómez, D. (2020). A web-based tool framing a collective method for optimizing the location of a renewable energy facility and its possible application to sustainable STEM education. *Journal of Cleaner Production*, *251*. https://doi.org/10.1016/j.jclepro.2019.119747

Jeong, J. S., & Ramírez-Gómez, Á. (2018). Optimizing the location of a biomass plant with a fuzzy-DEcision-MAking Trial and Evaluation Laboratory (F-DEMATEL) and multi-criteria spatial decision assessment for renewable energy management and long-term sustainability. *Journal of Cleaner Production*, *182*, 509–520. https://doi.org/10.1016/j.jclepro.2017.12.072

Kashanian, M., Pishvaee, M. S., & Sahebi, H. (2020). Sustainable biomass portfolio sourcing plan using multi-stage stochastic programming. *Energy*, *204*. https://doi.org/10.1016/j.energy.2020.117923

Kesharwani, R., & Sun, Z. (2018). *Biofuel supply chain optimal design considering economic , environmental , and societal aspects towards sustainability*. *January*, 2169–2198. https://doi.org/10.1002/er.4006

Kittler, B., Stupak, I., & Smith, C. T. (2020). *Assessing the wood sourcing practices of the U . S . industrial wood pellet industry supplying European energy demand*. *4*, 1–18.

Kolb, R. W. (2018). Asymmetric Information. *The SAGE Encyclopedia of Business Ethics and Society*, *20*(1), 92–115. https://doi.org/10.4135/9781483381503.n72

Kuo, T. C., Lin, S. H., Tseng, M. L., Chiu, A. S. F., & Hsu, C. W. (2019). Biofuels for vehicles in Taiwan: Using system dynamics modeling to evaluate government subsidy policies. *Resources, Conservation and Recycling*, *145*(February), 31–39. https://doi.org/10.1016/j.resconrec.2019.02.005

Lam, H. L., Ng, W. P. Q., Ng, R. T. L., Ng, E. H., Aziz, M. K. A., & Ng, D. K. S. (2013). Green strategy for sustainable waste-to-energy supply chain. *Energy*, *57*, 4–16. https://doi.org/10.1016/j.energy.2013.01.032

Lauven, L., Sowlati, T., & Geldermann, J. (2019). *Strategic planning of a multi-product wood-biore fi nery production system*. *211*, 1502–1516. https://doi.org/10.1016/j.jclepro.2018.12.004

Lei, Q., Chen, J., Wei, X., & Lu, S. (2015). Supply chain coordination under asymmetric production cost information and inventory inaccuracy. *International Journal of Production Economics*, *170*, 204–218. https://doi.org/10.1016/j.ijpe.2015.09.015

Leong, H., Leong, H., Foo, D. C. Y., Yin, L., & Andiappan, V. (2019). Hybrid approach for carbon-constrained planning of bioenergy supply chain network. *Sustainable Production and Consumption*, *18*, 250–267. https://doi.org/10.1016/j.spc.2019.02.011

Lim, C. H., How, B. S., Ng, W. P. Q., & Lam, H. L. (2019). Debottlenecking of biomass element deficiency in a multiperiod supply chain system via element targeting approach. *Journal of Cleaner Production*, *230*, 751–766. https://doi.org/10.1016/j.jclepro.2019.05.127

Lim, J. Y., How, B. S., Rhee, G., Hwangbo, S., & Yoo, C. K. (2020). Transitioning of localized renewable energy system towards sustainable hydrogen development

planning: P-graph approach. *Applied Energy*, *263*(January), 114635. https://doi.org/10.1016/j.apenergy.2020.114635

Lozano-moreno, J. A., & Mar, F. (2019). *Biomass logistics and environmental impact modelling for sugar-ethanol production*. *210*. https://doi.org/10.1016/j.jclepro.2018.10.310

Mahjoub, N., Sahebi, H., Mazdeh, M., & Teymouri, A. (2020). Optimal design of the second and third generation biofuel supply network by a multi-objective model. *Journal of Cleaner Production*, *256*, 120355. https://doi.org/10.1016/j.jclepro.2020.120355

Mai-moulin, T., & Visser, L. (n.d.). *Sourcing overseas biomass for EU ambitions : assessing net sustainable export potential from*. 293–324. https://doi.org/10.1002/bbb.1853

Malladi, K. T., & Sowlati, T. (2020). Bi-objective optimization of biomass supply chains considering carbon pricing policies. *Applied Energy*, *264*(February), 114719. https://doi.org/10.1016/j.apenergy.2020.114719

Mamun, S., Hansen, J. K., & Roni, M. S. (2020). Supply , operational , and market risk reduction opportunities : Managing risk at a cellulosic biorefinery. *Renewable and Sustainable Energy Reviews*, *121*(November 2019), 109677. https://doi.org/10.1016/j.rser.2019.109677

Marufuzzaman, M., Ek, S. D., & Hernandez, R. (2014). *Environmentally Friendly Supply Chain Planning and Design for Biodiesel Production via Wastewater Sludge*. *48*(4), 555–574.

Matopoulos, A., Wright, D. G., & Scott, J. (2018). *Integrated optimization of sustainable supply chains and transportation networks for multi technology bio-based production : A decision support system based on fuzzy ε -constraint method*. *172*, 2594–2617. https://doi.org/10.1016/j.jclepro.2017.11.150

Mauro, C., Rentizelas, A. A., & Chinese, D. (2018). International vs. domestic bioenergy supply chains for co-firing plants: The role of pre-treatment technologies. *Renewable Energy*, *119*, 712–730. https://doi.org/10.1016/j.renene.2017.12.034

Mazzetto, F., Simoes-Lucas, G., Ortiz-Gutiérrez, R. A., Manca, D., & Bezzo, F. (2015). Impact on the optimal design of bioethanol supply chains by a new European Commission proposal. *Chemical Engineering Research and Design*, *93*(May), 457–463. https://doi.org/10.1016/j.cherd.2014.05.006

Memari, A., Ahmad, R., Abdul Rahim, A. R., & Akbari Jokar, M. R. (2018). An optimization study of a palm oil-based regional bio-energy supply chain under carbon pricing and trading policies. *Clean Technologies and Environmental Policy*, *20*(1), 113–125. https://doi.org/10.1007/s10098-017-1461-7

Mohamed Abdul Ghani, N. M. A., Szmerekovsky, J. G., & Vogiatzis, C. (2020). Plant

capacity level and location as a mechanism for sustainability in biomass supply chain. In *Energy Systems* (Vol. 11, Issue 4). Springer Berlin Heidelberg. https://doi.org/10.1007/s12667-019-00361-z

Mohseni, S., & Pishvaee, M. S. (2020). Computers & Industrial Engineering Data-driven robust optimization for wastewater sludge-to-biodiesel supply chain design. *Computers & Industrial Engineering*, *139*(July 2019), 105944. https://doi.org/10.1016/j.cie.2019.07.001

Moncada, J. A., Verstegen, J. A., Posada, J. A., Junginger, M., Lukszo, Z., Faaij, A., & Weijnen, M. (2019). Exploring the emergence of a biojet fuel supply chain in Brazil: An agent-based modeling approach. *GCB Bioenergy*, *11*(6), 773–790. https://doi.org/10.1111/gcbb.12594

Mousavi Ahranjani, P., Ghaderi, S. F., Azadeh, A., & Babazadeh, R. (2018). Hybrid Multiobjective Robust Possibilistic Programming Approach to a Sustainable Bioethanol Supply Chain Network Design. *Industrial and Engineering Chemistry Research*, *57*(44), 15066–15083. https://doi.org/10.1021/acs.iecr.8b02869

Mousavi Ahranjani, P., Ghaderi, S. F., Azadeh, A., & Babazadeh, R. (2020). Robust design of a sustainable and resilient bioethanol supply chain under operational and disruption risks. In *Clean Technologies and Environmental Policy* (Vol. 22, Issue 1). Springer Berlin Heidelberg. https://doi.org/10.1007/s10098-019-01773-2

Mulyati, H., & Geldermann, J. (2017). Managing risks in the Indonesian seaweed supply chain. *Clean Technologies and Environmental Policy*, *19*(1), 175–189. https://doi.org/10.1007/s10098-016-1219-7

Muresan, M., Cormos, C. C., & Agachi, P. S. (2013). Techno-economical assessment of coal and biomass gasification-based hydrogen production supply chain system. *Chemical Engineering Research and Design*, *91*(8), 1527–1541. https://doi.org/10.1016/j.cherd.2013.02.018

Mutenure, M., Čuček, L., Egieya, J., Isafiade, A. J., & Kravanja, Z. (2018). Optimization of bioethanol and sugar supply chain network : a South African case study. *Clean Technologies and Environmental Policy*, *20*(5), 925–948. https://doi.org/10.1007/s10098-018-1535-1

Naeini, M. A., Zandieh, M., Najafi, S. E., & Sajadi, S. M. (2020). Analyzing the development of the third-generation biodiesel production from microalgae by a novel hybrid decision-making method: The case of Iran. *Energy*, *195*. https://doi.org/10.1016/j.energy.2020.116895

Nepal, S., & Tran, L. T. (2019). Identifying trade-offs between socio-economic and environmental factors for bioenergy crop production: A case study from northern Kentucky. *Renewable Energy*, *142*, 272–283. https://doi.org/10.1016/j.renene.2019.04.110

Nguyen, D. H., & Chen, H. (2018). Supplier selection and operation planning in

biomass supply chains with supply uncertainty. *Computers and Chemical Engineering*, *118*, 103–117. https://doi.org/10.1016/j.compchemeng.2018.07.012

No Title Environment Canada. (2016).

No Title Natural Resources Canada. (2012). *2012–2013 Report on Plans and Priorities.*

No Title Pan-Canadian Framework on Clean Growth and Climate Change. (2016). https://scics.ca/en/product-produit/pan-canadian-framework-on-clean-growth-and-climate-change/

Nodooshan, K. G., Moraga, R. J., Chen, S. G., Nguyen, C., Wang, Z., & Mohseni, S. (2018). *Environmental and Economic Optimization of Algal Biofuel Supply Chain with Multiple Technological Pathways*. https://doi.org/10.1021/acs.iecr.7b02956

Nugroho, Y. K., & Zhu, L. (2019). Platforms planning and process optimization for biofuels supply chain. *Renewable Energy*, *140*, 563–579. https://doi.org/10.1016/j.renene.2019.03.072

Nurariffudin, M., Idris, M., Hashim, H., & Hanim, N. (2018). Spatial optimisation of oil palm biomass co- fi ring for emissions reduction in coal- fi red power plant. *Journal of Cleaner Production*, *172*, 3428–3447. https://doi.org/10.1016/j.jclepro.2017.11.027

Osmani, A., & Zhang, J. (2013). Stochastic optimization of a multi-feedstock lignocellulosic-based bioethanol supply chain under multiple uncertainties. *Energy*, *59*, 157–172. https://doi.org/10.1016/j.energy.2013.07.043

Pakravan, M. H. (2020). *What Motivates Behavior Change ? Analyzing User Intentions to Adopt Clean Technologies in Low-Resource Settings Using the Theory of Planned Behavior*.

Palak, G., Ekşioğlu, S. D., & Geunes, J. (2014). Analyzing the impacts of carbon regulatory mechanisms on supplier and mode selection decisions: An application to a biofuel supply chain. *International Journal of Production Economics*, *154*(2014), 198–216. https://doi.org/10.1016/j.ijpe.2014.04.019

Palander, T., Haavikko, H., & Kärhä, K. (2018). Towards sustainable wood procurement in forest industry – The energy e ffi ciency of larger and heavier vehicles in Finland. *Renewable and Sustainable Energy Reviews*, *96*(August), 100–118. https://doi.org/10.1016/j.rser.2018.07.043

Pan, S. Y., Du, M. A., Huang, I. Te, Liu, I. H., Chang, E. E., & Chiang, P. C. (2015). Strategies on implementation of waste-to-energy (WTE) supply chain for circular economy system: a review. *Journal of Cleaner Production*, *108*, 409–421. https://doi.org/10.1016/j.jclepro.2015.06.124

Paolucci, N., Bezzo, F., & Tugnoli, A. (2016). A two-tier approach to the optimization of a biomass supply chain for pyrolysis processes. *Biomass and Bioenergy*, *84*, 87–97. https://doi.org/10.1016/j.biombioe.2015.11.011

Paredes-Sánchez, J. P., Conde, M., Gómez, M. A., & Alves, D. (2018). Modelling hybrid thermal systems for district heating: A pilot project in wood transformation industry. *Journal of Cleaner Production*, *194*, 726–734. https://doi.org/10.1016/j.jclepro.2018.05.170

Park, Y. S., Szmerekovsky, J., & Dybing, A. (2019). Optimal Location of Biogas Plants in Supply Chains under Carbon Effects: Insight from a Case Study on Animal Manure in North Dakota. *Journal of Advanced Transportation*, *2019*. https://doi.org/10.1155/2019/5978753

Pashaei, F., Augusto, J., Borges, R., Osseweijer, P., & Posada, J. A. (2018). Towards social sustainability : Screening potential social and governance issues for biojet fuel supply chains in Brazil. *Renewable and Sustainable Energy Reviews*, *92*(February), 50–61. https://doi.org/10.1016/j.rser.2018.04.078

Pavlou, D., Orfanou, A., Busato, P., Berruto, R., Sørensen, C., & Bochtis, D. (2016). Functional modeling for green biomass supply chains. *Computers and Electronics in Agriculture*, *122*, 29–40. https://doi.org/10.1016/j.compag.2016.01.014

Petridis, K., & Grigoroudis, E. (2018). *A goal programming model for a sustainable biomass supply chain network*. *12*(1), 79–102. https://doi.org/10.1108/IJESM-09-2017-0002

PriceWaterhouseCoopers, P. (2010). *No Title*. "Viewpoints of CEOs%0Ain the Forest, Paper & Packaging IndustryWorldwide (CEO%0APerspectives)".

Quddus, M. A., Ibne Hossain, N. U., Mohammad, M., Jaradat, R. M., & Roni, M. S. (2017). Sustainable network design for multi-purpose pellet processing depots under biomass supply uncertainty. *Computers and Industrial Engineering*, *110*, 462–483. https://doi.org/10.1016/j.cie.2017.06.001

Rabbani, M., Momen, S., Akbarian-saravi, N., & Farrokhi-asl, H. (2020). Optimal design for sustainable bioethanol supply chain considering the bioethanol production strategies : A case study. *Computers and Chemical Engineering*, *134*, 106720. https://doi.org/10.1016/j.compchemeng.2019.106720

Rabbani, M., Saravi, N. A., Farrokhi-Asl, H., Lim, S. F. W. T., & Tahaei, Z. (2018). Developing a sustainable supply chain optimization model for switchgrass-based bioenergy production: A case study. *Journal of Cleaner Production*, *200*, 827–843. https://doi.org/10.1016/j.jclepro.2018.07.226

Rahemi, H., Torabi, S. A., Avami, A., & Jolai, F. (2020). Bioethanol supply chain network design considering land characteristics. *Renewable and Sustainable Energy Reviews*, *119*(April 2018), 109517. https://doi.org/10.1016/j.rser.2019.109517

Razm, S., Nickel, S., & Sahebi, H. (2019). A multi-objective mathematical model to redesign of global sustainable bioenergy supply network. *Computers and Chemical Engineering*, *128*, 1–20. https://doi.org/10.1016/j.compchemeng.2019.05.032

Rebs, T., Brandenburg, M., & Seuring, S. (2018). System dynamics modeling for sustainable supply chain management : A literature review and systems thinking approach. *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2018.10.100

Rentizelas, A. A., Tatsiopoulos, I. P., & Tolis, A. (2009). An optimization model for multi-biomass tri-generation energy supply. *Biomass and Bioenergy*, *33*(2), 223–233. https://doi.org/10.1016/j.biombioe.2008.05.008

Rincon, L., Puri, M., Kojakovic, A., & Maltsoglou, I. (2019). The contribution of sustainable bioenergy to renewable electricity generation in Turkey: Evidence based policy from an integrated energy and agriculture approach. *Energy Policy*, *130*(January), 69–88. https://doi.org/10.1016/j.enpol.2019.03.024

Rivera-Cadavid, L., Manyoma-Velásquez, P. C., & Manotas-Duque, D. F. (2019). Supply chain optimization for energy cogeneration using sugarcane crop residues (SCR). *Sustainability (Switzerland)*, *11*(23). https://doi.org/10.3390/su11236565

Rogers, J. N., Incorporated, E., Stokes, B., Science, A., Dc, W., Dunn, J., Cai, H., & Wu, M. (2016). *An assessment of the potential products and economic and environmental impacts resulting from a billion ton bioeconomy*. https://doi.org/10.1002/bbb

Saadati, M., & Hosseininezhad, S. J. (2019). Biomass and Bioenergy Designing a hub location model in a bagasse-based bioethanol supply chain network in Iran (case study : Iran sugar industry). *Biomass and Bioenergy*, *122*(June 2018), 238–256. https://doi.org/10.1016/j.biombioe.2019.01.013

Saghaei, M., & Dehghanimadvar, M. (2020). *Optimization and analysis of a bioelectricity generation supply chain under routine and disruptive uncertainty and carbon mitigation policies*. *October 2019*, 2976–2999. https://doi.org/10.1002/ese3.716

Saghaei, M., Ghaderi, H., & Soleimani, H. (2020). Design and optimization of biomass electricity supply chain with uncertainty in material quality , availability and market demand. *Energy*, *197*, 117165. https://doi.org/10.1016/j.energy.2020.117165

Sahoo, K., Mani, S., Das, L., & Bettinger, P. (2018). GIS-based assessment of sustainable crop residues for optimal siting of biogas plants. *Biomass and Bioenergy*, *110*(April 2017), 63–74. https://doi.org/10.1016/j.biombioe.2018.01.006

Sánchez-Bautista, A. D. F., Santibanez-Aguilar, J. E., You, F., & Ponce-Ortega, J. M. (2017). Optimal Design of Energy Systems Involving Pollution Trading through Forest Plantations. *ACS Sustainable Chemistry and Engineering*, *5*(3), 2585–2604. https://doi.org/10.1021/acssuschemeng.6b02928

Sansaniwal, S. K., Rosen, M. A., & Tyagi, S. K. (2017). Global challenges in the sustainable development of biomass gasi fi cation : An overview. *Renewable and Sustainable Energy Reviews*, *80*(March 2016), 23–43. https://doi.org/10.1016/j.rser.2017.05.215

Santibañez-Aguilar, J. E., Ponce-Ortega, J. M., Betzabe González-Campos, J., Serna-González, M., & El-Halwagi, M. M. (2013). Optimal planning for the sustainable utilization of municipal solid waste. *Waste Management*, *33*(12), 2607–2622. https://doi.org/10.1016/j.wasman.2013.08.010

Sarkar, M., & Sarkar, B. (2020). How does an industry reduce waste and consumed energy within a multi-stage smart sustainable biofuel production system? *Journal of Cleaner Production*, *262*. https://doi.org/10.1016/j.jclepro.2020.121200

Seuring, S., & Gold, S. (2012). Conducting content-analysis based literature reviews in supply chain management. *Supply Chain Management*, *17*(5), 544–555. https://doi.org/10.1108/13598541211258609

Seuring, S., & Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. *Journal of Cleaner Production*, *16*(15), 1699–1710. https://doi.org/10.1016/j.jclepro.2008.04.020

Shabani, N., Akhtari, S., & Sowlati, T. (2013). Value chain optimization of forest biomass for bioenergy production: A review. *Renewable and Sustainable Energy Reviews*, *23*, 299–311. https://doi.org/10.1016/j.rser.2013.03.005

Shabani, N., & Sowlati, T. (2016). A hybrid multi-stage stochastic programming-robust optimization model for maximizing the supply chain of a forest-based biomass power plant considering uncertainties. *Journal of Cleaner Production*, *112*, 3285–3293. https://doi.org/10.1016/j.jclepro.2015.09.034

Shallo, L., Ayele, M., & Sime, G. (2020). *Determinants of biogas technology adoption in southern Ethiopia*. 1–14.

She, J. (2020). Multiobjective record - to - record travel metaheuristic method for solving forest supply chain management problems with economic and environmental objectives. *Natural Resource Modeling*, *December 2019*, 1–25. https://doi.org/10.1111/nrm.12256

Smith, D. J., Current, D., Schulman, C., & Easter, K. W. (2018). Willingness to produce perennial bioenergy crops: A contingent supply approach. *Biomass and Bioenergy*, *117*(August), 161–172. https://doi.org/10.1016/j.biombioe.2018.06.018

Song, J., Yang, W., Higano, Y., & Wang, X. (2015). Modeling the development and utilization of bioenergy and exploring the environmental economic benefits. *Energy Conversion and Management*, *103*, 836–846. https://doi.org/10.1016/j.enconman.2015.07.028

Soto-Silva, W. E., Nadal-Roig, E., González-Araya, M. C., & Pla-Aragones, L. M. (2016). Operational research models applied to the fresh fruit supply chain. *European Journal of Operational Research*, *251*(2), 345–355. https://doi.org/10.1016/j.ejor.2015.08.046

Sun, O., & Fan, N. (2020). A Review on Optimization Methods for Biomass Supply Chain: Models and Algorithms, Sustainable Issues, and Challenges and Opportunities. *Process Integration and Optimization for Sustainability*, *4*(3), 203–226. https://doi.org/10.1007/s41660-020-00108-9

Tan, Q., Wang, T., Zhang, Y., Miao, X., & Zhu, J. (2017). Nonlinear multi-objective optimization model for a biomass direct-fired power generation supply chain using a case study in China. *Energy*, *139*, 1066–1079. https://doi.org/10.1016/j.energy.2017.08.050

Taylor, P., Bernetti, I., Sacchelli, S., Sottini, V. A., & Marinelli, N. (2013). *International Journal of Sustainable Optimisation of the regional energy supply network : a multi-objective analysis in the province of Florence (Italy)*. *June*, 37–41. https://doi.org/10.1080/14786451.2013.811412

Tiammee, S., & Likasiri, C. (2020). Sustainability in corn production management: A multi-objective approach. *Journal of Cleaner Production*, *257*, 120855. https://doi.org/10.1016/j.jclepro.2020.120855

Touš, M., Pavlas, M., Stehlík, P., & Popela, P. (2011). Effective biomass integration into existing combustion plant. *Energy*, *36*(8), 4654–4662. https://doi.org/10.1016/j.energy.2011.04.036

Trujillo-Mata, A., Cortés-Robles, G., Sánchez-Ramírez, C., Blanco-Fernández, J., & Jiménez-Macías, E. (2018). System dynamics for the water footprint assessment and simulation in the bioethanol production. *International Journal of Simulation and Process Modelling*, *13*(4), 355–363. https://doi.org/10.1504/IJSPM.2018.093759

Tsao, Y., & Vu, T. (2019). Power supply chain network design problem for smart grid considering differential pricing and buy-back policies. *Energy Economics*, *81*, 493–502. https://doi.org/10.1016/j.eneco.2019.04.022

Vaccaro, G. L. R., Longhi, A., Moutinho, M. H. C., Scavarda, A., Lopes, C. M., dos Reis, A. N., Nunes, F., & Azevedo, D. (2018). Interrelationship among actors in ethanol production chain as a competitive and sustainable factor: The case of associative production and family-farming in southern Brazil. *Journal of Cleaner Production*, *196*, 1239–1255. https://doi.org/10.1016/j.jclepro.2018.06.036

Van Belle, J. F., Temmerman, M., & Schenkel, Y. (2003). Three level procurement of forest residues for power plant. *Biomass and Bioenergy*, *24*(4–5), 401–409. https://doi.org/10.1016/S0961-9534(02)00161-7

Van Holsbeeck, S., & Srivastava, S. K. (2020). Feasibility of locating biomass-to-bioenergy conversion facilities using spatial information technologies: A case study on forest biomass in Queensland, Australia. *Biomass and Bioenergy*, *139*(September 2019), 105620. https://doi.org/10.1016/j.biombioe.2020.105620

Varbanov, P. S., Walmsley, T. G., Fan, Y. V., Klemeš, J. J., & Perry, S. J. (2018). Spatial

targeting evaluation of energy and environmental performance of waste-to-energy processing. *Frontiers of Chemical Science and Engineering*, *12*(4), 731–744. https://doi.org/10.1007/s11705-018-1772-1

Vasković, S., Halilović, V., Gvero, P., Medaković, V., & Musić, J. (2015). Multi-criteria optimization concept for the selection of optimal solid fuels supply chain from wooden biomass. *Croatian Journal of Forest Engineering*, *36*(1), 109–124.

Vincevica-gaile, Z., Stankevica, K., Irtiseva, K., Shishkin, A., Obuka, V., Celma, S., Ozolins, J., & Klavins, M. (2019). Biomass and Bioenergy Granulation of fly ash and biochar with organic lake sediments – A way to sustainable utilization of waste from bioenergy production. *Biomass and Bioenergy*, *125*(March), 23–33. https://doi.org/10.1016/j.biombioe.2019.04.004

Vlachokostas, C., Achillas, C., Agnantiaris, I., Michailidou, A. V., Pallas, C., Feleki, E., & Moussiopoulos, N. (2020). Decision support system to implement units of alternative biowaste treatment for producing bioenergy and boosting local bioeconomy. *Energies*, *13*(9), 1–14. https://doi.org/10.3390/en13092306

Wang, X., Lim, M. K., & Ouyang, Y. (2017). Food-energy-environment trilemma: Policy impacts on farmland use and biofuel industry development. *Energy Economics*, *67*, 35–48. https://doi.org/10.1016/j.eneco.2017.05.021

WCED. (1987). *No Title*. World Commission on Environment and Development. https://sustainabledevelopment.un.org/content/documents/5987our-common-future.pdf

Wen, W., & Zhou, P. (2018). Impacts of regional governmental incentives on the straw power industry in China: A game-theoretic analysis. *Journal of Cleaner Production*, *203*, 1095–1105. https://doi.org/10.1016/j.jclepro.2018.08.149

Wheeler, J., Caballero, J. A., Ruiz-Femenia, R., Guillén-Gosálbez, G., & Mele, F. D. (2017). MINLP-based Analytic Hierarchy Process to simplify multi-objective problems: Application to the design of biofuels supply chains using on field surveys. *Computers and Chemical Engineering*, *102*, 64–80. https://doi.org/10.1016/j.compchemeng.2016.10.014

Wiens, M., Diehlmann, F., Zimmer, T., Gl, S., & Schultmann, F. (2019). *Techno-economic assessment of utilization pathways for rice straw : A simulation-optimization approach*. *230*. https://doi.org/10.1016/j.jclepro.2019.04.369

Wolde, B., Lal, P., & Burli, P. (2017). Forestland owners ' willingness to consider multiple ways of supplying biomass simultaneously : Implications for biofuel incentive policies. *Energy Policy*, *105*(March), 183–190. https://doi.org/10.1016/j.enpol.2017.02.040

Woo, H., Acuna, M., Moroni, M., Taskhiri, M. S., & Turner, P. (2018). Optimizing the location of biomass energy facilities by integrating Multi-Criteria Analysis (MCA) and Geographical Information Systems (GIS). *Forests*, *9*(10), 1–15. https://doi.org/10.3390/f9100585

Yang, R., Tang, W., Dai, R., & Zhang, J. (2018a). Contract design in reverse recycling supply chain with waste cooking oil under asymmetric cost information. *Journal of Cleaner Production*, *201*, 61–77. https://doi.org/10.1016/j.jclepro.2018.07.329

Yang, R., Tang, W., Dai, R., & Zhang, J. (2018b). Contract design in reverse recycling supply chain with waste cooking oil under asymmetric cost information. *Journal of Cleaner Production*, *201*, 61–77. https://doi.org/10.1016/j.jclepro.2018.07.329

Yang, R., Tang, W., & Zhang, J. (2020). Implications of government subsidies for waste cooking oil considering asymmetric information. *Kybernetes*, *50*(2), 588–615. https://doi.org/10.1108/K-10-2019-0708

Yang, R., Tang, W., & Zhang, J. (2021). Implications of government subsidies for waste cooking oil considering asymmetric information. *Kybernetes*, *50*(2), 588–615. https://doi.org/10.1108/K-10-2019-0708

Yazan, D. M., Cafagna, D., Fraccascia, L., Mes, M., Pontrandolfo, P., & Zijm, H. (2018). Economic sustainability of biogas production from animal manure: a regional circular economy model. *Management Research Review*, *41*(5), 605–624. https://doi.org/10.1108/MRR-02-2018-0053

Yazan, D. M., Fraccascia, L., Mes, M., & Zijm, H. (2018). Cooperation in manure-based biogas production networks: An agent-based modeling approach. *Applied Energy*, *212*(July 2017), 820–833. https://doi.org/10.1016/j.apenergy.2017.12.074

Yazan, D. M., van Duren, I., Mes, M., Kersten, S., Clancy, J., & Zijm, H. (2016). Design of sustainable second-generation biomass supply chains. *Biomass and Bioenergy*, *94*, 173–186. https://doi.org/10.1016/j.biombioe.2016.08.004

Ye, F., Cai, Z., Chen, Y. J., Li, Y., & Hou, G. (2020). Subsidize farmers or bioenergy producer? The design of a government subsidy program for a bioenergy supply chain. *Naval Research Logistics*, *July 2019*, 1–16. https://doi.org/10.1002/nav.21909

Ye, F., Li, Y., Lin, Q., & Zhan, Y. (2020). Modeling of China ' s cassava-based bioethanol supply chain operation and coordination. *Energy*, *120*(2017), 217–228. https://doi.org/10.1016/j.energy.2016.12.114

Ye, F., Li, Y., & Yang, Q. (2018). Designing coordination contract for biofuel supply chain in China. *Resources, Conservation and Recycling*, *128*, 306–314. https://doi.org/10.1016/j.resconrec.2016.11.023

Ye, F., Xie, Z., Cai, Z., & Lin, Q. (2020). Optimization of the biofuel supply chain with capital-constrained farmers under government subsidies. *IEEE Access*, *8*, 8178–8192. https://doi.org/10.1109/ACCESS.2019.2962585

Yilmaz Balaman, Ş., & Selim, H. (2014). A fuzzy multiobjective linear programming

model for design and management of anaerobic digestion based bioenergy supply chains. *Energy*, *74*(C), 928–940. https://doi.org/10.1016/j.energy.2014.07.073

Yılmaz Balaman, Ş., Scott, J., Matopoulos, A., & Wright, D. G. (2019). Incentivising bioenergy production: Economic and environmental insights from a regional optimization methodology. *Renewable Energy*, *130*(2019), 867–880. https://doi.org/10.1016/j.renene.2018.06.083

Yun, H., Clift, R., & Bi, X. (2020). *Process simulation , techno-economic evaluation and market analysis of supply chains for torrefied wood pellets from British Columbia : Impacts of plant conFigureuration and distance to market*. *127*(March 2019).

Zahraee, S. M., Golroudbary, S. R., Shiwakoti, N., Kraslawski, A., & Stasinopoulos, P. (2019). An investigation of the environmental sustainability of palm biomass supply chains via dynamic simulation modeling: A case of Malaysia. *Journal of Cleaner Production*, *237*, 117740. https://doi.org/10.1016/j.jclepro.2019.117740

Zhang, H., Li, L., Zhou, P., Hou, J., & Qiu, Y. (2014). Subsidy modes, waste cooking oil and biofuel: Policy effectiveness and sustainable supply chains in China. *Energy Policy*, *65*, 270–274. https://doi.org/10.1016/j.enpol.2013.10.009

Zhang, Yanan, Hu, G., & Brown, R. C. (2014). Integrated supply chain design for commodity chemicals production via woody biomass fast pyrolysis and upgrading. *Bioresource Technology*, *157*, 28–36. https://doi.org/10.1016/j.biortech.2014.01.049

Zhang, Yong, & Jiang, Y. (2017). Robust optimization on sustainable biodiesel supply chain produced from waste cooking oil under price uncertainty. *Waste Management*, *60*, 329–339. https://doi.org/10.1016/j.wasman.2016.11.004

Zhao, N., & You, F. (2019). Dairy waste-to-energy incentive policy design using Stackelberg-game-based modeling and optimization. *Applied Energy*, *254*(August), 113701. https://doi.org/10.1016/j.apenergy.2019.113701

Zhao, R., Liu, Y., Zhang, Z., Guo, S., Tseng, M., & Wu, K. (n.d.). *Enhancing Eco-Efficiency of Agro-Products ' Closed-Loop Supply Chain under the Belt and Road Initiatives : A System Dynamics Approach*. https://doi.org/10.3390/su10030668

Zheng, T., Wang, B., Rajaeifar, M. A., Heidrich, O., Zheng, J., Liang, Y., & Zhang, H. (2020). How government policies can make waste cooking oil-to-biodiesel supply chains more efficient and sustainable. *Journal of Cleaner Production*, *263*, 121494. https://doi.org/10.1016/j.jclepro.2020.121494

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