AN ABSTRACT OF THE THESIS OF

Javad Sadeghi for the degree of Master of Science in Industrial Engineering presented on May 31, 2018

Title: Assisting Sustainability Analysis of Forest Bioenergy Supply Chains using Mathematical Optimization

Abstract approved:

Karl R. Haapala

Changes in the global climate and forest management practices have given rise to increasing numbers and severity of wildfires. More than five million acres burned in the United States in 2017, while in Canada 7.4 million acres burned. In particular, an increasing amount of dead woody biomass is a key factor in forest fire hazards. The call for mitigating the effects of climate change, specifically focusing on reducing the risk of wildfires, has attracted considerable global attention toward renewable energy sources. The objective of this research is to provide decision makers in private industry and governmental agencies the ability to reliably assess economic, environmental, and social criteria simultaneously while optimizing bio-oil supply chains in managing the land and forests to decrease wildfire risks. An optimized biomass to bio oil supply chain is presented by using a mathematical problem considering economic, environmental, and social criteria. The focus of the application of this work is on northwest Oregon forests. The production of bio-oil is not only able to help mitigate climate change impacts such as forest fire hazards, but it can

also improve energy independence, employment opportunities, and economic development.

To extend prior related research, a single-objective mathematical model is first presented, which relaxes a limitation of prior mathematical models for bio-oil supply chain problems by considering carbon cost as a part of the total supply chain cost. Since the model is a mixed integer linear programming problem, a metaheuristic optimization approach (genetic algorithm) is designed to obtain an optimized solution. The proposed mathematical model can be applied in the design of a biomass to bio-oil supply chain including mobile refineries, in which total cost consists of logistics cost and carbon cost. Decision makers will be able to apply the proposed genetic algorithm for large scale problems to overcome restrictions of exact methods.

As the demand for sustainable supply chains continues, logistics problems must be designed to balance solutions across the three pillars of sustainability: the economy, environment, and society. Thus, a multi-objective mathematical model is next developed for a bio-oil supply chain, which includes six levels: harvesting sites, collection sites, mobile refineries, fixed refineries, distribution centers, and residential areas. The branch-and-cut search in CPLEX software solves the proposed model using data from northwest Oregon forests. The model obtains optimal values for three decision variables, i.e., mass of biomass to be transported, mass of bio-oil to be transported, and the facility locations, to simultaneously optimize total cost, carbon footprint, and number of jobs created. From evaluation of the model, it is found that supplementing a traditional bio-oil supply chain with mobile refineries has the potential to significantly reduce the cost of bio-oil. Sensitivity analysis is performed to evaluate the effect of key parameters on supply chain objectives under different scenarios. It was also found that the percentage yield parameter and mobile refinery capacity have a more significant effect on the selected objectives than the other parameters tested. Based on the supply chain modeling, the behavior of the predicted cost of bio-oil, carbon footprint, and number of jobs created is intuitive with respect to the changes in the model parameters. Further, the sensitivity analysis results show that the cost of bio-oil predicted by the mathematical model falls in the cost interval found in the market and research literature.

In addition to reducing wildfire risks and energy dependence by collecting combustible forest biomass, the research result shows that consideration of societal aspects in bio-oil supply chains can provide a competitive cost of bio-oil. Exploration of mobile refineries is a focus here to elucidate bio-oil supply chain sustainability performance through mathematical modeling, and has not been previously reported in literature. The lack of access to the conversion processes prevented a more accurate estimation of the cost of bio-oil. To improve this limitation, modeling the parameters of bio-oil supply chains using stochastic approaches in future research would allow for a more in-depth investigation of tradeoffs between objectives.

ASSISTING SUSTAINABILITY ANALYSIS OF FOREST BIOENERGY SUPPLY CHAINS USING MATHEMATICAL OPTIMIZATION

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CONTRIBUTION OF AUTHORS

Chapter 3: Manuscript 1

Dr. Karl Haapala contributed to the development of the methodology to incorporate environmental impact criteria (carbon footprinting and carbon costing) and the writing of the manuscript. He also provided input and direction to the work and helpful review and feedback.

Chapter 4: Manuscript 2

Dr. Karl Haapala contributed to the development of the methodology to incorporate broader sustainability metrics (number of jobs created, local employment, total cost, and carbon footprint) and the writing of the manuscript. He also provided input and direction to the work and helpful review and feedback.

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CHAPTER 1: INTRODUCTION

This chapter presents an introduction for the research developed herein. An overview of the research domain and background of the specific research topic area are presented. Moreover, the research objective, research tasks, and outline of the thesis are presented.

1.1 Overview

Due to recent lengthening of wildfire seasons worldwide (Jolly et al., 2015), a call has been made by society to assist private and governmental organizations in managing the land and forests to decrease wildfire risks. Over the last three decades, the US experienced no significant change in the number of wildfires, while the total acreage burned has been significantly increasing (Landis et al., 2017). Around five million acres of forests burned in the US in 2017 (Pierre-Louis, 2017); and fires in Oregon accounted for one half million of these acres. The wildfire problem is highlighted by the destruction of homes and loss of other property, but it has other significant direct and indirect impacts on the society and environment, e.g., human injury or death, and damage to infrastructure, wildlife habitats, and water quality (Edgeley & Paveglio, 2017). Wildfire damage has been estimated to cost the US economy tens to hundreds of billions of dollars, annually (Fann et al., 2018). The ubiquity of wildfires demands societal attention to find a solution for mitigating this problem (Landis et al., 2017).

How then can we decrease wildfire hazards? One answer is to address the presence of dried woody forest biomass, which is a key contributor to fire hazards (Madrigal et al., 2017). As a potential viable solution to reducing wildfire risks, combustible forest biomass can be collected and removed for generating renewable energy sources, such as bio-oil (Madrigal et al., 2017). In addition to decreasing environmental impacts of fire hazards, value creation from underutilized woody forest biomass benefits society and the economy (Hubbard, Biles, Mayfield, & Ashton, 2007), which align with the three pillars of sustainability.

Conceptually, the three pillars of sustainability involves the integration of the economic, environmental, and social aspects (Hansmann, Mieg, & Frischknecht, 2012). The economic aspect considers financial performance of human systems, the environmental aspect focuses on the effects of human activities on the natural environment, and the social aspect investigates the well-being of people. Many methods have been introduced to assess these three aspects individually or jointly. It is widely agreed that all three must be simultaneously considered to provide the sustainable performance of a product (Giddings, Hopwood, & O'Brien, 2002; Lozano, 2008).

1.2 Background

As a result of the industrial revolution, human activities have created harmful effects on the environment and society to the point that human extinction is plausible (Pearson, 2001). Sustainable supply chain management (SCM) is presented as an innovative solution to curtail these negative effects (Seuring, 2013). Seuring and Müller (2008) defined sustainable SCM as:

> [T]he management of material, information and capital flows as well as cooperation among companies along the supply chain while taking goals from all three dimensions of sustainable development, i.e., economic, environmental and social, into account which are derived from customer and stakeholder requirements.

This definition by Seuring and Müller is innovative in that it goes beyond typical single and two-factor combinations, and considers the economic, environmental, and social factors in SCM decisions. However, their definition is not without issues. For instance, Carbo et al. (2014) posited that it is difficult to apply the theory of sustainability to industrial problems because capitalism is dependent upon continuous economic growth, often at the expense of the environment and social stability. Thus, they suggested that our economic system should be reformed to reduce the focus on monetary costs. Decision makers must be able to trade between economic, environmental, and social factors to address these issues simultaneously. In particular, a multi-objective sustainable SCM approach is suited to separately optimizing the economic, environmental, and the social aspects, using three different objectives.

1.3 Problem Overview

In sum, US forests are experiencing an increasing risk of forest fires, while bio-oil supply chains have the potential to reduce wildfire risks by removing dried woody forest biomass. However, due to market and policy uncertainties, bio-oil supply chains have undergone protracted development (Hong, How, & Lam, 2016). In particular, it has been suggested that existing supply chain analysis methods are not able to sufficiently consider meeting economic, environmental, societal goals, simultaneously (Seuring, 2013). Current bio-oil supply chain analysis approaches focus on only minimizing monetary costs, which may lead to negative impacts on the environment and society. The research herein is motivated to mitigate this problem.

1.4 Research Objective

The objective of this research is to provide decision makers in private industry and governmental agencies the ability to reliably assess economic, environmental, and social criteria simultaneously while optimizing bio-oil supply chains in managing the land and forests to decrease wildfire risks.

1.5 Research Tasks

In response to decrease wildfire risks by collecting of combustible forest biomass, the overall purpose of this research is to support optimization of biomass to bio-oil supply chains. This will be accomplished by using a multi-objective mathematical problem that considers economic, environmental, and social criteria. Several research tasks are undertaken to fulfill the objective of this research.

The first task is to develop a single-objective mathematical model for bio-oil supply chain optimization that incorporates environmental impacts. Subtasks include reviewing prior studies to understand bio-oil supply chain model functionality, developing a mathematical model to quantify total cost of bio-oil production, and designing a genetic algorithm for optimizing mixed supply chain problems.

The second task is to develop a multi-objective mathematical model to assist the simultaneous optimization of a set of sustainability metrics for bio-oil supply chains. Subtasks include conducting background research for understanding biomass to bio-oil logistics functionality, collecting model-supporting data, applying theoretical equations to quantify sustainability metrics, using an optimization approach to solve the developed mathematical model, and analyzing the assessment results.

1.6 Thesis Outline

This research is reported in the manuscript format and includes five chapters. Chapter 1 provides the overview, motivation, objective, and tasks of this research. Chapter 2 reviews the literature on multi-objective models in sustainable supply chains.

Chapter 3 is a journal article submitted to the Journal of Operations Research & Decision Theory and titled "Optimizing a Sustainable Logistics Problem in a Renewable Energy Network Using a Genetic Algorithm." This article develops a mathematical model that can be used to simultaneously optimize renewable energy supply chain logistics costs and carbon footprint. The proposed model considers a biomass to bio-oil supply chain, including harvesting and collection sites, bio refineries, and distribution centers.

Chapter 4 is a journal article to be submitted to the Journal of Transportation Research Part E: Logistics and Transportation Review, and titled "A Three-Objective Mathematical Logistics Model for Integrating a Mobile Facility into a Sustainable Bio-Oil Supply Chain." This article develops the methodology presented in Chapter 3 to model a multi-objective problem for bio-oil supply chains based on data derived from a case study of bio-oil production for forest biomass in northwest Oregon.

Chapter 5 presents the summary, conclusions, and contributions of this research, and proposes opportunities for future work. Finally, Appendix A and Appendix B report the MATLAB and CPLEX source codes, respectively, for solving the mathematical models.

CHAPTER 2: LITERATURE REVIEW

This section considers the prior research in sustainable supply chain models to presents the limitation and gaps of bio-oil problem studies.

2.1 Sustainability and Supply Chain Management

Two sets of activities form the bio-oil production network: the conversion process and logistics activities. The work presented herein focuses on logistics activities undertaken in the bio-oil supply chain. Prior research (published after 2008) exploring quantitative problems in sustainable supply chain management were identified by searching the Web of Science, comprised of multiple scientific databases (Web of Science, 2018). For interested readers, five prior studies (Abbasi & Nilsson, 2016; Guo, Shen, Choi, & Jung, 2017; Gupta & Palsule-Desai, 2011; Ilgin & Gupta, 2010; Seuring, 2013) provide a comprehensive review of supply chain management through 2017.

The first researchers to consider the societal effects of sustainable SCM were Pérez-Fortes et al. (2012). They used a mathematical model for sustainability analysis that accounts for the number of jobs created in the supply chain. To measure the environmental effects discussed in their case study, they used life-cycle assessment (LCA). They evaluated the tradeoffs between sustainability criteria using a multi-objective mathematical model in a biomass-to-rural electrification supply chain, which includes sourcing, pre-treatment, electricity generation, and distribution. The considered storage used in their model altered the biomass characteristic (e.g., heating value, dry matter, and moisture content). They employed an ε-constraint method using GAMS software to provide an optimal solution, which included biomass utilization, matter transportation, biomass storage periods, connectivity between the supply entities, and the location and capacity of gasification. In their recommendations for further research, they mentioned two possibilities: (1) The addition of mathematical models of pre-treatment and storage processes to extend their sustainable SCM approach; and (2) A decomposition approach to improve the solution algorithm.

In addition to focusing on job creation, wealth can serve as another indicator of societal effects in sustainability analysis. In fact, Boukherroub et al. (2015) suggested job creation and wealth as indicators of societal effects in a study of the Canadian lumber industry. In logistics modeling, they assumed that third-party logistics providers transported the products. They used a weighted goal-programming algorithm to optimize a mathematical model that included raw materials utilization, inventory levels, and the number of employees.

Improving economic development ─ calculated by regional economic value and regional development factor ─ is another societal consideration that has been explored alongside job creation. For example, in a sustainable pharmaceutical case study, Zahiri et al. (2017) employed a multi-objective evolutionary algorithm to optimize a sustainable SCM including manufacturers, distribution centers, and demand zones. Their total cost included selling and buying technology products, carbon credits, transportation, and capital, as well as inventory holding costs. The second objective considered the societal impact in terms of job creation and economic development. The environmental objective was to minimize the carbon footprint of the supply chain. Based on their case study, they suggested that improving the supply chain optimization algorithm from a sustainability perspective and developing a mathematical model to consider perishable products should be pursued as future research.

Job creation, wealth, and economic development are not the only indicators that have been considered to define societal impact. Ramos et al. (2014), for example, explored maximum working hours as an indicator of societal impact in a recyclable waste collection chain. They used carbon footprint to consider the environmental effects. For mathematical modeling of the supply chain, they utilized the vehicle-routing approach with different delivery patterns for customers. They also employed an augmented ε-constraint method using CPLEX to provide the optimal solution to the decision maker. For future work, they suggested performing a sensitivity analysis to study the behavior of parameters.

Another societal effect that has been considered in sustainability analysis is the total lead-time indicator (the sum of transportation and processing times). Zhang et al. (2014) focused on minimizing total lead time in a chemical product supply chain. For the supply chain, which included production plants and suppliers, the researchers developed a mathematical model to find an optimal solution for improving the three pillars of sustainability. The optimal solution included allocation and material flows between supply chain echelons for cost, lead time, and greenhouse gas emissions. To extend their proposed model, they suggested future research consider multi-period sustainable SCM with regard to inventory management and time-dependent demand.

Researchers have drawn upon the foundational work done by Pérez-Fortes et al. (2012) by applying their indicators to different case studies. In a biomass case study in British Columbia, Canada, Cambero and Sowlati (2016) proposed a multi-objective sustainable SCM, in which there were different types of raw materials from a set of supply sources for a set of locations to produce a product. To provide a set of solutions for the mathematical model, they used an augmented ε-constraint method in AIMMS software. As future work, they suggested developing the model using stochastic programming.

Based on the future research directions suggested by Cambero and Sowlati (2016) and Pérez-Fortes et al. (2012), Osmani and Zhang (2017) extended a biomass supply chain model to include stochastic parameters and the Benders decomposition algorithm for a three-echelon sustainable supply chain. Different types of raw materials were transferred from a set of sources to a set of locations to produce a final product. To overcome the uncertainties in a case study for Wisconsin, USA, they assumed the amount raw materials, demand for the final product, and the sale price to be probability parameters with known statistical distributions. To extend their research, they suggested investigating more indicators for evaluating societal impacts.

2.2 Limitations of Prior Research and Research Question

In addition to the sustainability supply chains discussed above (consolidated in Table 1), several studies have considered the relationships between logistics costs and production costs (e.g., (Mirkouei, Haapala, Sessions, & Murthy, 2017; Yue, You, & Snyder, 2014a)). In particular, facility cost has seen much attention in recent publications, and bio-refinery costs have been identified as the primary cost driver in bio-energy supply chains (Mirkouei et al., 2017). Another key supply chain cost is due to transportation, which is directly linked to facility locations. An extensive body of literature in multi-objective sustainable SCM focuses on networks with fixed facility locations. However, a limitation that has received little attention is the inability of a fixed facility-based supply chain to deal with fluctuating demand and raw materials, e.g., due to seasonal variation. Relying on fixed facilities often will not generate a reliable solution. This motivates the need for research to examine the effect of mobile facilities, e.g., mobile refineries, on supply chain costs.

Table 2.1: Studies in multi-objective sustainable supply chains

Authors	The Model Application	Contribution
Pérez-Fortes et al. (2012)	Biomass; rural electrification	Storage conditions change biomass properties
Zhang et al. (2014)	Chemical products in Michigan, USA	Lead time objective
Ramos et al. (2014)	Recyclable waste collection	A new solution approach, balanced workload
Boukherroub et al. (2015)	Canadian lumber industry	Wealth, climate change
Cambero and Sowlati (2016)	Biomass; electricity, heat, bio-oil, pellets	An indicator to assess the overall job-related social benefit
Osmani and Zhang (2017)	Biomass in Wisconsin, USA	Decomposition approach, stochastic programming
Zahiri et al. (2017)	Pharmaceutical case study in France	Fuzzy-stochastic programming, hybrid algorithm
Model proposed in chapter 4	Biomass in Oregon, USA	Mobile-facility, carbon footprint, operating costs

In multi-objective sustainable SCM problems, previous studies focusing on modeling sustainability indicators through mathematical models have failed to address the following question. How can a decision support tool be designed to aid facility location and production decisions with regard to three sustainability objectives (i.e., total supply chain cost, carbon footprint, and number of jobs created) for a supply chain using a mix of mobile and fixed facilities?

The work presented herein tries to answer this question by proposing a three-objective mathematical model based on data derived from a case study of bio-oil production for forest biomass in northwest Oregon. This data allows us pose three specific questions: What is the predicted cost of bio-oil based on total supply chain cost? How do bio-oil supply chain decisions affect the number of employees working in refineries? What is the carbon footprint of a bio-oil supply chain?

Chapter 3: Optimizing a Sustainable Logistics Problem in a Renewable Energy Network Using a Genetic Algorithm

by
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CHAPTER 3: OPTIMIZING A SUSTAINABLE LOGISTICS PROBLEM IN A RENEWABLE ENERGY NETWORK USING A GENETIC ALGORITHM

3.1 Abstract

Renewable energy sources, including bio-energy technologies, have been introduced to overcome sustainability challenges, such as negative environmental impacts and energy insecurity due to reliance on fossil fuels. Logistics activities have a significant effect on the cost and environmental impacts of renewable energy supply chains. Understanding and reducing the carbon footprint of renewable energy supply chains can aid in mitigating environmental impacts. Thus, this research presents a mathematical model that can be used to optimize renewable energy supply chain logistics costs and carbon footprint. The proposed model considers a biomass to bio-oil supply chain, including harvesting and collection sites, bio refineries, and distribution centers. It is assumed that mobile and fixed refineries will be used to produce bio-oil. The model considers the mass of biomass and bio-oil, number of mobile and fixed refineries, and number of truck trips to minimize total cost, where a carbon tax is used to represent carbon footprint in the mathematical cost model. A genetic algorithm is designed to obtain a near optimal solution. Six scenarios for mobile and fixed refinery capacity are tested in performing sensitivity analysis of the model. The results indicate that the mathematical model of the bio-oil supply chain has reasonable relationships between input and output variables. The model is able to incorporate the impact of carbon emissions in a mixed-refinery bio-oil supply chain as a cost parameter. It was also found that increasing mobile refinery capacity has the greater effect on reducing total cost and carbon emissions than increasing fixed refinery capacity.

3.2 Introduction

In recent years, supply chain management (SCM) principles have been applied to reduce total production system cost. SCM integrates several parts of a logistics-manufacturing network to obtain an optimal or near-optimal decision. It is vital for decision makers to simultaneously consider all parts of a network due to trade-offs that may occur when considering parts of the system independently. Warehousing, for example, desires to hold lower product inventory levels to reduce holding costs, while sales attempts to have higher inventory levels to avoid losses of sales. SCM aids in managing the flow of goods in a system by assisting in decisions about production, inventory, location, logistics, and delivery with respect to constraints on the system.

With a growing call for sustainable industrial development, which is as an approach to provide society with responsible products, SCM principles have been applied to address existing barriers, such as resource constraints and competing industrial demands. A surge of interest can be seen in assessing the sustainability performance of supply chain activities (Alsaffar, Raoufi, Kim, Okudan Kremer, & Haapala, 2016). As a part of sustainable industrial development, sustainable manufacturing has been described by the U.S. Department of Commerce as, “creation of a manufactured product with processes that have minimal negative impact on the environment, conserve energy and natural resources, are safe for employees and communities, and are economically sound” (Garretson, Mani, Leong, Lyons, & Haapala, 2016). A particular area of interest over the past half century has been in reducing the use of fossil fuel-based energy, due to concerns over energy security and environmental impacts of extraction, processing, and use, among other reasons

(Coram & Katzner, 2018).

The burning of fossil fuels by humans has a critical role in changing the proportions of atmosphere gases leading to global warming. Renewable energy sources (e.g., bioenergy, solar energy, and wind energy) have been explored as alternatives to fossil-based energy for the past several decades (No, 2014). According to the *REN21 Renewables Global Status Report*, little progress has been made, with renewable energy only comprising 19.3% of global energy consumption in 2017 (REN21, 2017). While a limited number of countries have readily accessible fossil fuel energy sources, many regions are able to provide renewable energy resources. Thus, the need for efficient, low-cost, and environmentally-responsible production of renewable energy has attracted considerable attention globally.

Bio-oil is considered a source of clean, renewable energy (Pantone et al., 2017). Bio-oil, a dark brown organic liquid, also called bio-fuel oil, pyrolytic oil, liquid wood, and pyrolysis oil, is produced by pyrolysis of biomass (Isahak, Hisham, Yarmo, & Hin, 2012). Pyrolysis involves the high thermal decomposition of organic material in the absence of oxygen (or any halogen). Chemical, biochemical, and thermal methods can be used to produce bio-oil from biomass. Woody biomass is often used to produce bio-oil. Traditional biomass (e.g., forest harvest residues, energy crops, and agricultural residues) comprises a high proportion (47%) of the renewable energy consumption (REN21, 2017). Forest residue is one of the most geographically distributed biomass energy resources (Ng'andwe, Mwitwa, & Muimba-Kankolongo, 2015), and is attracting the attention of companies to produce bio-oil. One advantage of bio-oil is that it can be directly used in boilers as fuel (Isahak et al., 2012). In addition, utilizing dead woody materials from forests to produce bio-oil offers a low-cost solution that can help bioenergy industries to grow, while also reducing forest fire risks (Woodall et al., 2013). According to the Oregon Department of Forestry, more than 500,000 acres burned in Oregon in 2017 (Lehman, 2017).

The biomass-to-bio-oil supply chain (BTBSC) consists of two sets of operations: conversion and logistics. The first set of operations involves all decisions relevant to activities for efficient conversion of biomass to bio-oil (e.g., process settings and production scheduling). The second set of operations, which we focus on here, focuses on improving decisions relevant to transportation and warehousing.

Recent growing interest within society over the use of renewable resources for bioenergy has stimulated research efforts in improving biomass processing solutions (Cutz, Haro, Santana, & Johnsson, 2016) and balancing the sustainability dimensions in logistics (Osmani & Zhang, 2017). Mobile refineries have been proposed to overcome logistics challenges in BTBSCs, such as high handling and transportation costs due to biomass properties (bulky and low energy density). Mobile bio-refineries can enable more efficient transport systems. Instead of trucking biomass to a fixed bio-refinery, mobile bio-refinery units are transferred to the forest or farms to convert biomass feedstocks to intermediate products (e.g., bio-oil and bio-char). There are three main advantages of employing mobile refineries in BTBSCs (Mirkouei, Mirzaie, Haapala, Sessions, & Murthy, 2016): (i) decreasing the total cost including fixed, variable, and labor costs; (ii) reducing the required storage capacity for biomass; (iii) reducing transportation costs. In particular, four factors have been identified that influence the benefits of employing mobile refineries: transportation distances, biomass type, policies and regulations, and time of the year.

Due to the challenges related to the use of fossil fuels noted above, it seems reasonable to understand the potential of alternative energy sources to reduce energy costs and carbon footprint. Prior research has investigated the effect of introducing mobile refineries into a conventional BTBSC by optimizing the supply chain based on logistics costs. However, research has not considered the impact of the cost of carbon on the structure and cost of mixed BTBSCs (employing fixed and mobile refineries). The research presented herein proposes a mathematical modeling approach to simultaneously consider the factors of logistics and energy policy (carbon price) in the cost optimization of a mixed BTBSC. To complete such an optimization, the structure of the supply chain and its associated carbon footprint need to be understood.

In a BTBSC, there are three main sources contributing to carbon footprint: logistics, conversion processes, and employee commuting (Boukherroub et al., 2015). In addition to logistics costs, the cost of associated carbon emissions are considered here by extending prior research (Mirkouei et al., 2016). Specifically, this research builds on the prior work by integrating the cost of a carbon into the mathematical cost model as a decision variable in the objective function. In addition, this work employs a metaheuristic method (a genetic algorithm) for the optimization of the proposed BTBSC, while the prior work used an exact optimization solver (Gurobi).

The remainder of this paper is structured as follows: Section 3.3 provides a brief review of related work; Section 3.4 presents the assumptions required for modeling, as well as a description of the problem to be formulated. The solution algorithm is given in Section 3.5. Section 3.6 presents an application of the model. Finally, conclusions based on this work and opportunities for future research are given in Section 3.7.

3.3 Prior Research

Two prior papers have reported comprehensive literature reviews on biomass-to-bioenergy supply chain optimization through 2016. Yue et al. (2014b) evaluated opportunities and key issues of BTBSCs with regard to sustainability factors, optimization methods, and mathematical models. Thereafter, Mirkouei et al. (2017) carried out a fundamental review to examine approaches and methodologies used in BTBSC. For example, Zhu et al. (2011) proposed a mixed integer linear programming (MILP) model for a numerical problem derived from the literature for the production of biofuel from biomass. Their problem involved two potential refinery locations, three potential storage locations, and ten biomass production fields. They solved the proposed mathematical model using CPLEX software. They considered one harvesting season (one year of operation) in managing a four-echelon supply chain, which included biomass production, harvesting, biofuel production, and storage. With regard to the importance of using mobile refineries in BTBSCs, Mirkouei et al. (2016) proposed a quantitative decision making approach. They presented an MILP model, solved by exact software (Gurobi), to obtain an optimal solution including the location of refineries, quantity of biomass and bio-oil, and a number of trips using a set of forest data from northwest Oregon. They showed that using mobile refineries leads to the reduction of system costs when transportations costs are high. In recent studies, while multi-objective problems have attracted much attention, use of mobile refineries has been ignored. Osmani and Zhang (2017), for example, presented a multi-objective mathematical model with data derived from Wisconsin, in which the sale price, demand, and the amount raw materials were assumed to be probability parameters with known statistical distributions. Table 3.1 compares the research reported herein and the approached used in prior work. No prior studies were identified in the literature that designed a genetic algorithm for solving mobile refinery problems with carbon cost included in the total cost of BTBSCs. The next section presents a mathematical model to optimize logistics costs and environmental impacts in a renewable energy supply chain.

Table 3.1: Relevant studies

Studies	Model	CO_2 e	Solution Algorithm	Mobile Refinery	Carbon Cost
Zhu et al. (2011)	MILP	-	Optimizer solver: CPLEX	-	-
Mirkouei et al. (2016)	MILP	-	Optimizer solver: Gurobi	Yes	-
Osmani and Zhang (2017)	Stochastic MILP	Objective	Optimizer solver: GAMS	-	-
Present Study	MILP	Variable	Metaheuristic Approach: Genetic Algorithm	Yes	Yes

3.4 The Proposed Mathematical Model

Most mathematical models used in transportation and logistics problems are formulated as mixed integer linear programming (MILP) problems. This section presents an MILP for a five-echelon BTBSC, including harvesting and collection sites, mobile and fixed refineries, and warehouses or distribution centers.

3.4.1 The Problem Statement

The five-echelon biomass-to-bioenergy network considered is shown in Figure 3.1. To produce the final product (bio-oil) from woody biomass, the total cost includes logistics and carbon costs. Four truck types are assumed to be used in the network due to road restrictions: small tractor-trailers, large tractor-trailers, small tanker trucks, and large tanker trucks. Small tractor-trailers are used to transport biomass from harvesting sites to collection sites. They are also used to transport material from harvesting sites to mobile refineries. Biomass is sent from collection sites to mobile and fixed refineries using large tractor-trailers. Small tanker trucks are used to transport bio-oil from mobile refineries to fixed refineries, while bio-oil is transferred from fixed refineries to warehouses using large tanker trucks. Notably, this research considers the upstream and midstream segments in BTBSC, while the downstream segment, including distribution and demand activities, is left to future work. Since the problem was formulated in a deterministic environment, stochastic parameters such as demand should also be considered in the future models.

Several other factors must be considered in formulating the mathematical model. Biomass type, moisture content, and ash content, for example, affect production yield in biomass-to-bio-oil conversion. In addition, costs of refinery operation consist of transport and setup costs (mobile refineries only), feedstock handling cost, purchased energy cost, and repair and maintenance costs. The variable, fixed, and labor costs of harvesting, collection, and pre-processing activities consist of the associated costs of employing a harvester, forwarder, and grinder, respectively (Mirkouei et al., 2016). A third-party transportation business is assumed to be used. Further, the type of truck for each route and the available amount of biomass at each site are known. The time horizon is assumed to be one year.

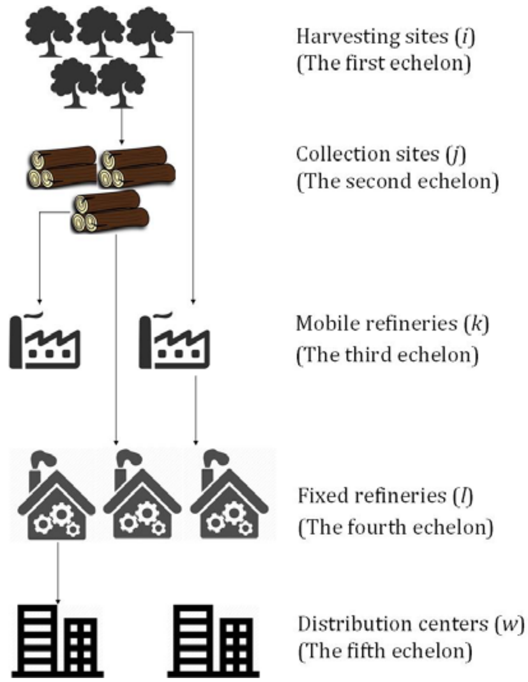

Figure 3.1: Five-echelon biomass-to-bioenergy network

3.4.2 The Mathematical Model

The mathematical model is presented below with regard to the BTBSC problem defined in Section 3.4.1. In this model, all parameters and variables are assumed to be deterministic. The notations of indices, parameters, and variables used in the mathematical model are as follows.

Indices:

i Set of harvesting sites, $i = 1, \ldots, I$,

j Set of collection sites, $j = 1, \ldots, J$,

k Set of mobile bio-refinery sites, $k = 1, \ldots, K$,

l Set of fixed bio-refinery sites, $l = 1, \ldots, L$,

t Set of time periods, $t = 1,\ldots, T$,

w Set of warehousing sites, $w = 1,\ldots, W$,

Parameters:

a The lowest allowable level of biomass utilization,

A Capacity of sites (*j*, *k*, *l*, and *w*) to store biomass or bio-oil,

c^l Capacity of large tractor-trailer,

c^s Capacity of small tractor-trailer,

c^{tl} Capacity of large tanker truck,

c^{ts} Capacity of small tanker truck,

C_t Total operation cost at time *t* for sites for *j*, *k*, *l*, and *w*,

D Distance between locations, e.g., D_{ij} indicates distance between site *i* and *j*,

e^l The full-load fuel consumption rate of large tractor-trailer,

e^s The full-load fuel consumption rate of small tractor-trailer,

e^{tl} The full-load fuel consumption rate of large tanker truck,

e^{ts} The full-load fuel consumption rate of small tanker truck,

f_{ij}^t The fuel consumption from the i^{th} node to the j^{th} node in the t^{th} period,

M Large positive constant (Big M),

P Percentage yield of converting biomass to bio-oil,

p^l Cost per mile for large tractor-trailer,

p^s Cost per mile for small tractor-trailer,

p^{tl} Cost per mile for large tanker truck,

p^{ts} Cost per mile for small tanker truck,

u Carbon tax/price,

Binary Decision Variables:

L_{jt} Binary variable to select the location of collection sites at time *t*, 1 indicates the location is selected, and 0 indicates the location is not selected,

L_{kt} Binary variable to select the location of mobile refinery sites at time *t*,

L_{lt} Binary variable to select the location of fixed refinery sites at time *t*,

L_{wt} Binary variable to select the location of collection sites at time *t*,

Decision Variables:

X_{ijt} Amount of biomass transported from site *i* to site *j* at time *t*,

X_{ikt} Amount of biomass transported from site *i* to site *k* at time *t*,

X_{jlt} Amount of biomass transported from site *j* to site *l* at time *t*,

X_{jkt} Amount of biomass transported from site *j* to site *k* at time *t*,

Y_{klt} Amount of bio-oil transported from site *k* to site *l* at time *t*,

Y_{lwt} Amount of bio-oil transported from site *l* to site *w* at time *t*, Cost Functions:

FC The facility costs,

TC The transportation costs,

TCC The total carbon cost.

The objective function includes two types of costs: logistics costs and carbon cost (Eq. (3.6)). Logistics costs include facility costs (Eq. (3.1)) and transportation costs (shown in Eq. (3.2)). The cost function is presented below in a piecewise manner.

The five primary activities considered (i.e., harvesting, collection, mobile refinery production, fixed refinery production, and warehousing) are completed in five different locations. The locations of harvesting sites and the mass of available raw material are known. However, the optimal locations for biomass collection, mobile refining, fixed refining, and warehousing are unknown. Thus, a set of four binary decision variables is used to determine the optimal location of each activity from the potential locations provided. To show the status of a location, a binary variable (*L*) is defined, where $L=1$ indicates the location is active, while $L=0$ indicates the location is inactive. With regard to total cost at time *t* (C_t) for each location, the facility costs (*FC*) are as follows (Eq. (3.1)):

$$\text{FC} = \sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{w=1}^{W}\left(C_{jt}L_{jt}+C_{kt}L_{kt}+C_{lt}L_{lt}+C_{wt}L_{wt}\right) \tag{3.1}$$

In order to calculate the transportation cost, the routes and number of trips between locations must be known. The number of truck trips is calculated by rounding up the total amount (mass or volume) of the product (biomass, *X*, and bio-oil, *Y*) being transported divided by the capacity of the truck (*c*) transporting the product between each location. With regard to distance between locations (*D*), cost per mile for trucks (*p*), and the amount of product being transported, the transportation cost (*TC*) is given as (Eq. (3.2)):

$$TC = TC \text{ of biomass} + TC \text{ of bio-oil} \tag{3.2}$$

in which,

$$\text{TC of bio-oil} = \sum_{t}^{T}\left(\sum_{k}^{K}\sum_{l}^{L} p^{ts} D_{kl}\left\lceil \frac{Y_{klt}}{c^{ts}} \right\rceil + \sum_{l}^{L}\sum_{w}^{W} p^{tl} D_{lw}\left\lceil \frac{Y_{lwt}}{c^{tl}} \right\rceil\right) \tag{3.3}$$

$$\text{TC of biomass} = \sum_{t}^{T}\left(\sum_{i}^{I}\sum_{j}^{J} p^{s} D_{ij}\left\lceil \frac{X_{ijt}}{c^{s}} \right\rceil + \sum_{i}^{I}\sum_{k}^{K} p^{s} D_{ik}\left\lceil \frac{X_{ikt}}{c^{s}} \right\rceil + \sum_{j}^{J}\sum_{k}^{K} p^{l} D_{jk}\left\lceil \frac{X_{jkt}}{c^{l}} \right\rceil + \right.$$

$$\left. \sum_{j}^{J}\sum_{l}^{L} p^{l} D_{jl}\left\lceil \frac{X_{jlt}}{c^{l}} \right\rceil\right) \tag{3.4}$$

In this model, carbon cost is calculated assuming a carbon tax rate (\$/kg CO_2) multiplied by the mass of CO_2 emissions generated by the trucks. It can be noted, “A carbon tax is a fee for making users of fossil fuels pay for climate damage their fuel use imposes by releasing carbon dioxide into the atmosphere, and for motivating switches to clean energy” (Carbon Tax Center, 2016). Total CO_2 emissions caused by the transportation network are calculated using a constant-speed approach (Cheng, Qi, Wang, & Zhang, 2016; Dilek, Karaer, & Nadar, 2018). Generally, three parameters are used to define a truck’s fuel consumption: speed, mass of load, and travel distance (Cheng et al., 2016). If the truck speed is constant, the fuel consumption from the i^{th} node to the j^{th} node in the t^{th} period, f_{ij}^{t}, without considering the return route can be estimated as follows (Cheng et al., 2016;

Dilek et al., 2018):

$$f_{ij}^{t} = D_{ij} e^{s} X_{ijt} \big/ c^{s} \tag{3.5}$$

in which, e^{s} indicates the full-load fuel consumption rate of a small tractor-trailer.

If u indicates the carbon tax, the total carbon cost (TCC) is predicted as:

$$\text{TCC} = u\sum_{t}^{T}\left(\sum_{i}^{I}\sum_{j}^{J} f_{ij}^{t} + \sum_{i}^{I}\sum_{j}^{J} f_{ik}^{t} + \sum_{i}^{I}\sum_{j}^{J} f_{jk}^{t} + \sum_{i}^{I}\sum_{j}^{J} f_{jl}^{t} + \sum_{i}^{I}\sum_{j}^{J} f_{kl}^{t} + \sum_{i}^{I}\sum_{j}^{J} f_{lw}^{t} \right) \tag{3.6}$$

According to the aforementioned equations related to costs, the objective function to minimize total cost is:

$$\text{Min } TC \; = FC + TC + TCC \tag{3.7}$$

Subject to (Eqs. (3.8-3.21)):

$$\sum_{l \in L} X_{jlt} + \sum_{k \in K} X_{jkt} = \sum_{i \in I} X_{ijt} \qquad \forall j \in J, t \in T \tag{3.8}$$

$$\sum_{i \in I} Y_{klt} = P \times \sum_{i \in I} X_{ikt} \qquad \forall k \in K, t \in T \tag{3.9}$$

$$\sum_{w \in W} Y_{lwt} = P \times \sum_{j \in J} X_{jlt} \qquad \forall l \in L, t \in T \tag{3.10}$$

$$\sum_{i \in I} X_{ijt} \le M \times L_{jt} \qquad \forall j \in J, t \in T \tag{3.11}$$

$$\sum_{i \in I} X_{ikt} + \sum_{j \in J} X_{jkt} \le M \times L_{kt} \qquad \forall k \in K, t \in T \tag{3.12}$$

$$\sum_{j \in J} X_{jlt} + \sum_{k \in K} Y_{klt} \le M \times L_{lt} \qquad \forall l \in L, t \in T \tag{3.13}$$

$$\sum_{l \in L} Y_{lwt} \le M \times L_{wt} \qquad \forall w \in W, t \in T \tag{3.14}$$

$$\sum_{i \in I} X_{ijt} \leq A_j \qquad \forall j \in J, t \in T \qquad (3.15)$$

$$\sum_{i \in I} X_{ikt} + \sum_{j \in J} X_{jkt} \leq A_k \qquad \forall k \in K, t \in T \qquad (3.16)$$

$$\sum_{j \in J} X_{jlt} \leq A_l \qquad \forall l \in L, t \in T \qquad (3.17)$$

$$\sum_{l \in L} \left(Y_{lwt} + \sum_{k \in K} Y_{klt} \right) \leq A_w \qquad \forall w \in W, t \in T \qquad (3.18)$$

$$\sum_{t \in T} \left(\sum_{i \in I} \sum_{j \in J} X_{ijt} + \sum_{i \in I} \sum_{k \in K} X_{ikt} \right) \geq a \qquad \forall t \in T \qquad (3.19)$$

$$X_{ijt}, X_{ikt}, X_{jkt}, X_{jlt}, Y_{klt}, Y_{lwt} \geq 0 \qquad \forall i \in I, j \in J, l \in L, k \in K, w \in W, t \in T \qquad (3.20)$$

$$L_{jt}, L_{kt}, L_{lt}, L_{wt} = \begin{cases} 1 & \text{if location is open,} \\ 0 & \text{otherwise.} \end{cases} \qquad \forall j \in J, k \in K, l \in L, w \in W, t \in T \qquad (3.21)$$

Eq. (3.8) represents the conservation of flow in and out of node *j*. Eqs. (3.9-3.10) present the conversion rate of biomass to bio-oil. Eqs. (3.11-3.14) show the status of locations (active or inactive) (*M* is a large positive constant). Eqs. (3.15-3.18) show the capacity constraint for each location. Eq. (3.19) indicates that the available amount of biomass in all harvesting sites should be used. Eqs. (3.20-3.21) present the decision variables. Section 3.5 proposes a genetic algorithm to find the decision variables X_{ijt}, X_{ikt}, X_{jkt}, X_{jlt}, Y_{klt}, Y_{lwt}, L_{jt}, L_{kt}, L_{lt}, and L_{wt} for optimizing the objective function presented in Eq. (3.7) with regard to the model constraints.

3.5 Solution Algorithm: Meta-heuristic Optimization

MILP models for large scale problems are unable to be solved by exact methods or solver software due to their complexity, which is NP hard (Tian, Ma, & Zhang, 1998). Metaheuristic approaches, which are also called approximate algorithms (Blum, Puchinger, Raidl, & Roli, 2011), are the most powerful for optimizing MILP models (El-ghazali Talbi, 2009). Metaheuristic algorithms are classified as single-based search, which start with a single candidate solution, and population-based search, which start with a population of candidate solutions (El-ghazali Talbi, 2009). Population-based methods usually outperform single-based search methods in speed and accuracy (Blum et al., 2011). To solve the mathematical model presented here, therefore, a genetic algorithm (GA) is employed. GA is the most powerful population-based method for solving MILP models (Yokota, Gen, & Li, 1996).

In GA terminology, a chromosome, which is a set of genes, a candidate for the solution is called. A chromosome consists of the decision variables. The genetic algorithm creates a random chromosome in a population as the solution of the problem, and then improves the solution with operators named “crossover” and “mutation” in a defined iteration (El-ghazali Talbi, 2009). In this research, the GA parameters are the probability of “two-point crossover” and “random mutation”, population size, and the number of iteration steps. The chromosome of this problem is designed as a matrix, including the decision variables. The GA is developed by language programming of MATLAB 2017b (see Appendix A), and solved using a Windows 10 64-bit Operation System with Intel Core i5 processor (CPU 3.40GHz) and 16GB RAM.

$$X_{ijt} = \begin{bmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} \\ X_{21} & X_{22} & X_{23} & X_{24} & X_{25} \\ X_{31} & X_{32} & X_{33} & X_{34} & X_{35} \\ X_{41} & X_{42} & X_{43} & X_{44} & X_{45} \end{bmatrix}_t = \begin{bmatrix} 13 & 63 & 12 & 0 & 9 \\ 25 & 43 & 23 & 63 & 22 \\ 13 & 122 & 212 & 434 & 545 \\ 123 & 20 & 40 & 100 & 500 \end{bmatrix}_t \tag{3.22}$$

The chromosome matrix includes the following decision variables: X_{ijt}, X_{ikt}, X_{jkt}, X_{jlt}, Y_{klt}, Y_{lwt}, L_{jt}, L_{kt}, L_{lt}, and L_{wt}, which utilize direct values, rather than being coded. Eq. (3.22) shows the X_{ijt} chromosome for four harvesting sites (rows) and five collection sites (columns).

$$\begin{array}{cc} \mathit{Parent}\,1 & \mathit{Parent}\,2 \\ \left[\begin{array}{cc|c} 12 & 34 & \underline{56} \\ 78 & 90 & \underline{12} \\ 13 & 14 & \underline{15} \end{array}\right] & \left[\begin{array}{cc|c} 11 & 22 & \boxed{33} \\ 44 & 55 & \boxed{66} \\ 77 & 88 & \boxed{99} \end{array}\right] \\ \\ \mathit{Child}\,1 & \mathit{Child}\,2 \\ \begin{bmatrix} 12 & 34 & \boxed{33} \\ 78 & 90 & \boxed{66} \\ 13 & 14 & \boxed{99} \end{bmatrix} & \begin{bmatrix} 11 & 22 & \underline{56} \\ 44 & 55 & \underline{12} \\ 77 & 88 & \underline{15} \end{bmatrix} \end{array}$$

Figure 3.2: Schematic of the single-point crossover method

As noted above, the process of creating two parent solutions and then producing a child solution using both is called crossover. There are several methods to perform crossover: single-point crossover, two-point crossover, uniform crossover, half uniform crossover, and three-parent crossover, to name a few. In this research, one-point crossover is used to create new generations, as shown in Figure 3.2. The vertical lines in the parent matrices represent the points of crossover. The selected genes, which are to the right of the vertical lines and indicated using underlined and boxed text, are swapped between the parents, creating the two children.

$$\text{Initial matrix} = \begin{bmatrix} \underline{13} & 63 & 12 & 0 & 9 \\ 25 & 43 & \underline{23} & 63 & 22 \\ 13 & \underline{122} & 212 & 434 & 545 \\ 123 & 20 & 40 & \underline{100} & 500 \end{bmatrix}$$

$$\downarrow \text{mutation}$$

$$\text{Mutated matrix} = \begin{bmatrix} \boxed{0} & 63 & 12 & 0 & 9 \\ 25 & 43 & \boxed{50} & 63 & 22 \\ 13 & \boxed{101} & 212 & 434 & 545 \\ 123 & 20 & 40 & \boxed{300} & 500 \end{bmatrix}$$

Figure 3.3: Schematic of the uniform mutation method

To select chromosomes from among the population as parents for crossover or as candidates for mutation, there are several selection methods, including “simplex crossover”, “tournament”, and “rank” selection (Gen & Cheng, 1997). This research uses tournament selection to choose an individual chromosome from the population, due to suitable coding efficiency (Miller & Goldberg, 1995). Pseudo code for tournament selection method is as follows:

- Randomly select g individuals (the tournament size) from the population,
- Select the best individual from the pool, with probability q (between 0 and 1),
- Select the second best individual, with probability $q \times (1-q)$,
- Select the third best individual, with probability $q \times (1-q)^2$.

A constrained optimization problem, such as used herein, can be solved with GA using penalty methods. Penalty methods convert constrained problems into unconstrained problems, and the provided solutions are valid for the original constrained problem. This research uses the death penalty method to obtain feasible solutions for the constrained problem. The death penalty method does not discard solutions, rather it introduces a penalty into the objective function when the solution obtained does not satisfy the constraints. The obtained solution is penalized by multiplying the constraint violations by penalty parameters.

3.6 Application of the Model

In this section, small and large test problems are first presented to demonstrate the convergence of the model, and then a sensitivity analysis of bio-refinery capacity is conducted to test the behavior model.

3.6.1 Small and Large Test Cases

In this section, two test problems (small and large) are solved with regard to the designed chromosome to be used in the GA. The test problems are used to evaluate the ability of the GA to repeatably converge to a near-optimal solution. The small test problem includes three harvesting sites, five collection sites, seven potential mobile refinery sites, eight potential fixed refinery sites, and two distribution sites. The large test problem includes twenty harvesting sites, eight collection sites, six potential mobile refinery sites, four potential fixed refinery sites, and two distribution sites. The latitude and longitude values for the potential locations were randomly generated. It is assumed that the four types of trucks noted above are available for transporting biomass and bio-oil. The mathematical model employs six sets of continuous decision variables, four sets of binary decision variables, and 14 sets of constraints for a set of locations (i, j, k, l, w), as defined by the general formulation provided above.

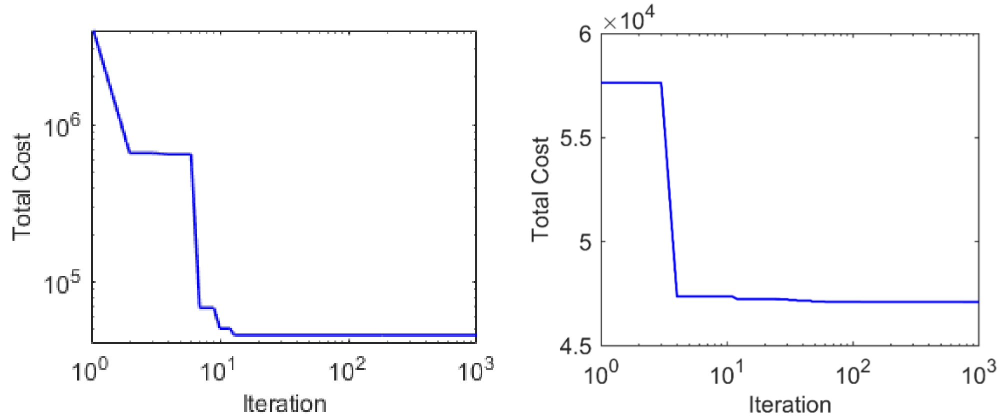

Figure 3.4: Lowest total cost obtained for each iteration (indicating convergence of the GA): Small test problem (left) and large test problem (right)

The technical parameter values used in metaheuristic algorithms affect the solver performance and the solution obtained. For the test problems, the values of the four parameters used, population, probability of crossover, probability of mutation, and number of iterations are 100, 0.8, 0.05, and 1000, respectively. These values were tuned by trial and error, which was more appropriate for the test problems than using published values. For the small and large test problems, the lowest total cost ("best cost") for each iteration is presented in Figure 3.4. It can be concluded that the GA converges to provide a near-optimal solution for the model presented in Eq. (3.7). There is not a significant reduction in the total cost obtained after the 140th iteration.

Figure 3.5 shows the lowest cost network found by the GA for the small bio-oil supply chain, which includes three collection sites, one mobile-refinery, three fixed-refineries, and one warehouse.

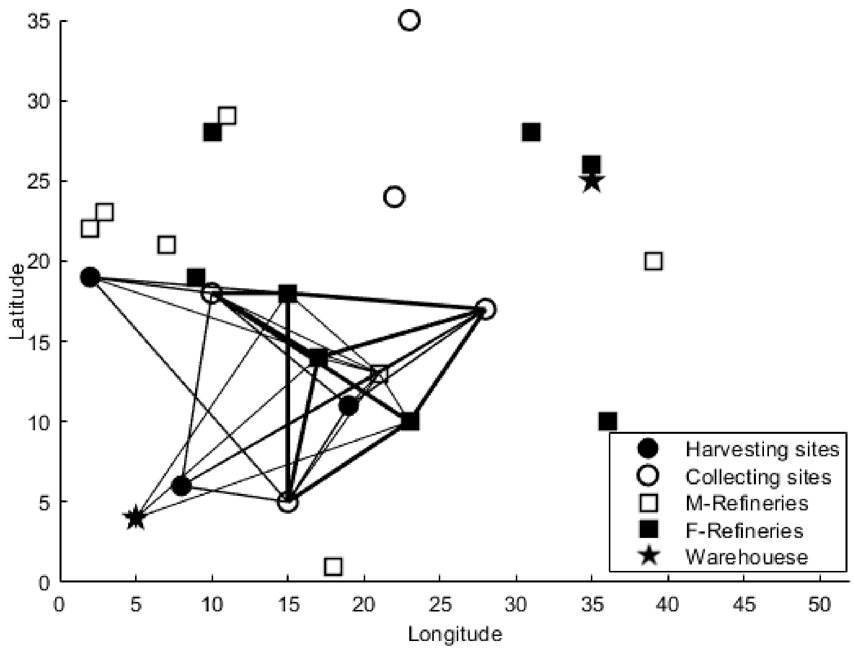

Figure 3.5: The identified optimal network (other potential locations for the small test problem also indicated)

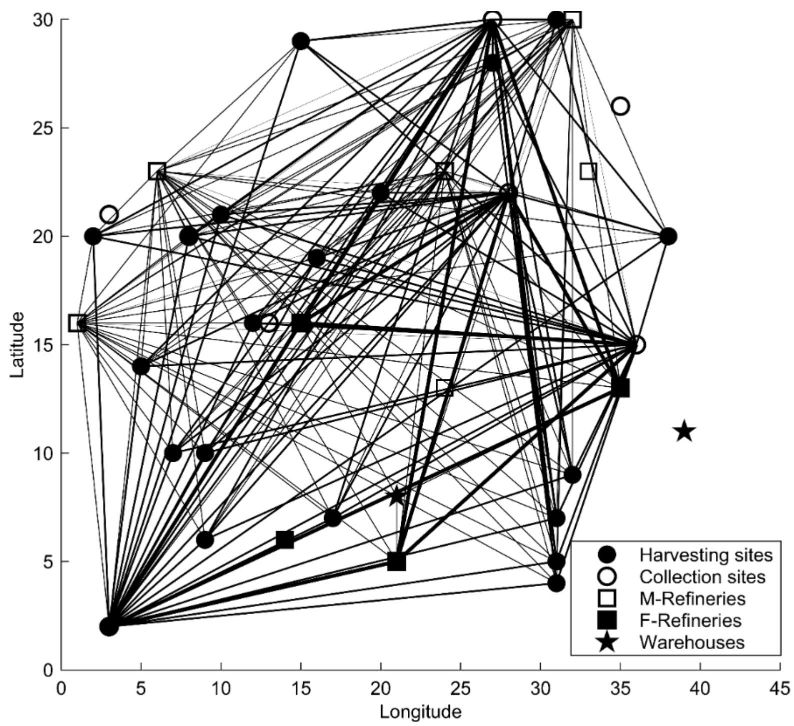

Figure 3.6: The optimal solution presented by GA with the potential locations for the large test problem

These optimal locations were selected from the set of potential locations (three harvesting sites, five collection sites, seven potential mobile refinery sites, eight potential fixed refinery sites, and two distribution sites), which are also indicated in the figure. Figure 3.6 shows the lowest cost network found by the GA for the large bio-oil supply chain, which is comprised of four collection sites, four mobile-refinery, three fixed-refineries, and one warehouse. These locations were optimally selected from the set of potential locations (twenty harvesting sites, eight collection sites, six potential mobile refinery sites, four potential fixed refinery sites, and two distribution sites), which are also indicated in the figure.

3.6.2 Sensitivity Analysis

Sensitivity analysis is performed to study the effect of the selected mathematical model inputs, which can vary, on the output of the model. Different scenarios are considered by varying model parameter values to observe the behavior of model. In general, when no constraints are placed on the capacities of harvesting and collection sites, mobile and fixed refineries, and warehouses, only one location will be selected from each set of collection, fixed refinery, mobile refinery, and warehouse locations. This result shows the expected behavior of the proposed mathematical model to optimize total cost by reducing the cost of active centers (selecting one location for processing and one location for storage). When we increase facility cost, fewer facilities will be selected. The total cost increases as a result of increasing cost parameters, e.g., transportation costs, carbon tax, and operating costs. Table 3.2 and Table 3.3 report the different scenarios for the capacity of refineries. Scenario 1 in Table 3.2 indicates a case in which a refinery has a capacity such that is able to store all of the incoming biomass from the harvesting and collection sites. In Scenario 2, the total cost and the number of active mobile refineries increase when mobile refinery capacity decreases by 35%. The same characteristic is seen for Scenario 3 and Scenario 4.

Table 3.2: Four scenarios exploring the effect of mobile refinery capacity on supply chain cost and active entities

Scenario	Capacity	Variability in capacity	Variability in costs	AMR	AFR	ACS	AWS
1	850	0%	0%	1	1	1	1
2	550	-35%	14%	2	1	1	1
3	300	-65%	36%	3	1	2	1
4	200	-76%	77%	5	1	3	1

AMR (active mobile-refinery); AFR (active fixed-refinery); ACS (active collection site); AWS (active warehouse site)

With regard to the original case (Scenario 1) in Table 3.3, Scenario 5 indicates the total cost and the number of fixed refineries increase when fixed refinery capacity decreases by 76%. When one fixed refinery does not have sufficient capacity to process all biomass, the bio-oil supply chain will require additional fixed refineries until the capacity is met, resulting in a cost increase (35% increase in Scenario 1). The same characteristic is seen for Scenario 2 (57% cost increase for a decrease in capacity of 85%).

Table 3.3: Three scenarios for the capacity of fixed refineries

Scenario	Capacity	Variability in capacity	Variability in costs	AMR	AFR	ACS	AWS
0	850	0%	0%	1	1	1	1
1	200	-76%	35%	1	2	2	1
2	130	-85%	57%	2	2	3	1

AMR (active mobile-refinery); AFR (active fixed-refinery); ACS (active collection site); AWS (active warehouse site)

According to the results of the sensitivity analysis, it can be said that the mathematical model presented in Eq. (3.7) has reasonable relationships between input and output variables. No errors with the model were identified, as no unexpected behaviors were revealed during the sensitivity analysis.

3.7 Conclusions

More than 500,000 acres of forests burned in Oregon in 2017, presumed to be due to changes in climate and forest management practices. Increased collection of dying and dead woody biomass from forests could help reduce fire hazards. This research drew inspiration from this impactful problem. A mathematical modeling approach was presented for optimizing the total cost of a biomass to bio-oil supply chain. The mathematical model was based on a five-echelon supply chain comprised of harvesting sites, collection sites, mobile refineries, fixed refineries, and warehouses. To extend prior related research, the model presented here relaxed a limitation of mathematical models for bio-oil supply chain problems by considering carbon cost as a part of the total supply chain cost. The aim of mathematical cost modeling was to find a near-optimal solution, including the number of truck trips, mass of biomass processed, mass of bio-oil produced, number of mobile and fixed refineries, and number of warehouses. Since the proposed model is a mixed integer linear programming problem, a meta-heuristic optimization approach (genetic algorithm) was designed to find an optimized solution.

By evaluating two test cases (small and large) and conducting a sensitivity analysis, it was shown that the proposed mathematical model can be applied in the design of a biomass to bio-oil supply chain including mobile refineries. Decision makers will be able to select the optimal number of mobile and fixed refineries with regard to total cost, which consists of logistics cost and carbon cost. Based on the presented approach, the mass of carbon emissions is first estimated to calculate the related carbon tax. Since the proposed methodology uses a genetic algorithm, it can be applied for large scale problems to overcome restrictions of exact methods.

Several limitations of mathematical modeling for biomass to bio-oil supply chains should be addressed by future research. The model presented herein was formulated in a deterministic environment. As shown in the sensitivity analysis, the proposed model does not have robustness in the presence of uncertainty. To address this limitation, stochastic parameters could be included in the mathematical model. Alternatively, design of experiments approaches, such as the Taguchi method, would aid in better calibrating the genetic algorithm parameters than tuning through trial and error. Although the GA converged to provide a near-optimal solution, exact methods by using CPLEX software can be applied to verify the provided solution in future research. As a key limitation of this research to perform more comprehensive sustainability assessment, only economic (supply chain cost) and environmental (carbon emissions) were included in the model, both represented as costs. The solution obtained by the genetic algorithm was optimized without considering broader economic, environmental, and social effects. Future research should address extensions of the mathematical model to simultaneously improve economic, environmental, and social performance of bioenergy supply chains.

Chapter 4: A Three-Objective Mathematical Logistics Model for Integrating a Mobile Facility into a Sustainable Bio-Oil Supply Chain

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CHAPTER 4: A THREE-OBJECTIVE MATHEMATICAL LOGISTICS MODEL FOR INTEGRATING A MOBILE FACILITY INTO A SUSTAINABLE BIO-OIL SUPPLY CHAIN

4.1 Abstract

In addition to mitigating fire hazards and climate change, improving forest biomass logistics can support energy independence and social quality by promoting renewable energy and creating jobs. A three-objective mathematical model is proposed for a six-level supply chain for the production of bio-oil from woody biomass in the northwestern United States. The logistics problem considers the three pillars of sustainability by modeling total cost, carbon footprint, and number of jobs created. Results indicate that the mobile facility approach can significantly reduce final product cost. Sensitivity analysis of selected model parameters was performed to determine their effect on chosen supply chain indicators.

4.2 Introduction

The increasing cost and detrimental effects of continued fossil fuel usage requires us to focus on renewable energies such as bio-oil (Pantone et al., 2017). In addition to reducing wildfire risk by removing excess biomass from forests, the resulting bio-oil from biomass conversion can be a potential alternative for fossil fuels. Bio-oil production involves two sets of activities: conversion processes (thermochemical activities including pyrolysis, gasification, and liquefaction (Demirbas, 2009)) and logistics (managing the flow of materials and goods). To optimally manage material flows in a renewable energy network, supply chain management (SCM) offers innovative approaches. A biomass to bio-oil supply chain (BTBSC) model considers all different parts of a system simultaneously with a wide-view throughout the chain.

Further focusing on sustainable development encourages decision makers to improve society (e.g., reducing both unemployment and crime rates, while improving education and training) in addition to improving the environment and the economy. This focus highlights sustainable supply chains as a globally urgent need. In particular, improving the economic sector (e.g., maximizing supply chain profitability) without considering other social aspects can give rise to negative societal effects. For example, in the documentary Roger & Me (Moore, 1989) the decision by General Motors executives to reduce 30,000 jobs with the purpose of increasing corporate profits, caused societal problems such as crime and poverty. Increases in unemployment rate negatively (Soler, Sanz, Caselles, & Micó, 2018) impacts education (Lavrinovicha, Lavrinenko, & Teivans-Treinovskis, 2015), crime and safety (Fallahi & Rodríguez, 2014). Studies found that the societal costs of unemployment include an increase in the number of unmarried people (Sasaki, 2017) and an increase in divorce rates (Amato & Beattie, 2011). A combination of intrinsic (such as opening/closing plants within the US) and extrinsic (such as fossil fuel prices dictated by global markets) factors have an effect on the unemployment rate. For example, a tradeoff has been shown between the unemployment rate and fossil fuel price, such that the natural rate of unemployment increases with increasing oil prices (Cuestas & Gil-Alana, 2018). Therefore, a solution should be proposed to reduce dependence on oil imports, while enabling the creation of new jobs. Renewable and alternative energy sources offer a potential for reducing energy dependency, harmful environmental impacts, and new economic development. Development of bio-oil supply chains, integral to the development of renewable energy, is a solution to reducing the unemployment rate by creating direct (e.g., machine operators, truck drivers, and production facility personnel) and indirect jobs (e.g., retail, financial services, real estate).

Improving the economy is a consistent ultimate common goal of all nations. The state's wealth has a significant effect on being able to address and mitigate societal problems. It is well known that a strong correlation exists between the economy, environment, and society. Scholarly critics claim that societal and environmental aspects are always considered under the purview and priority of cost (Carbo et al., 2014). This view may overlook the negative effects of a myopic cost focus on society and the environment. To address this problem, various approaches have been introduced. One, in particular, focuses on investments in renewable energy using multi-objective models (Fazlollahi, Mandel, Becker, & Maréchal, 2012). This can be a solution to alleviate the aforementioned problem, so that objectives (environment, society and economy) will be optimized separately without considering other objectives.

The research herein is motivated by the need to optimize biomass to bio-oil supply chains including mobile refineries using a multi-objective mathematical problem in regard to the three pillars of sustainability: environment, society, and economy. Current bio-oil supply chains are not sufficiently considered in meeting sustainability goals. Previous research, such as reported by Mirkouei et al. (2016), presented methods to reduce the cost and environmental impacts of bio-oil supply chains, by integrating mobile and fixed refineries and by optimizing total supply chain cost from harvesting sites to distribution centers. However, the societal effect of bio-oil supply chains utilizing fixed and mobile refineries and the environmental effect of carbon emissions during the conversion process have remained unanswered. Thus, these are a focus of the research reported in this paper.

The remainder of this paper is structured as follows: Section 4.3 provides the problem statement and mathematical model. Case study and data are given in Section 4.4. Section 4.5 presents the results and sensitivity analysis. Finally, opportunities for future research and conclusions are presented in Section 4.6.

4.3 Methodology

In mathematical optimization, mixed integer linear programming is usually employed to consider sustainable SCM problems. To simultaneously optimize the three objectives posed above, a multi-objective model is presented here. There are three dependent variables: total cost, carbon footprint, and number of jobs created, as well three independent variables: amount of biomass to be transported, amount of bio-oil to be transported, and facility locations.

To verify the mathematical model, real data is collected for northwest Oregon’s forests from the literature and ArcGIS software using databases provided by the US Forest Service, Oregon Department of Transportation, and State of Oregon Geospatial Enterprise Office. The shortest routes are calculated using an application programming interface (API) provided by Google using R-studio language programming. By using CPLEX software, the branch and cut method is able to provide optimized values (a set of Pareto solutions) for selected variables. Using sensitivity analysis, 32 scenarios are explored to show the performance of this decision-making method for producing bio-oil from biomass in northwest Oregon forests. The following sub-sections describe the formulation of the objectives, variables, and constraints in detail.

Assuming a deterministic environment, we consider a bio-energy supply chain in which bio-oil is produced from woody biomass collected from Oregon forests. In the considered biomass to bio-oil supply chain with a heterogeneous fleet (involving four types of trucks, V=4), there are six sets of locations, as shown in Figure 4.1 (harvesting sites i, collection sites k, mobile refineries j, fixed refineries l, warehouses w, and employee residential areas a). The distance between each pair of locations (D) is defined.

Available biomass at the harvesting sites (X_i) can be delivered to collection sites or mobile refineries with small tractor-trailers. Collection sites play the role of biomass depots. Therefore, a large volume of woody biomass can be delivered to fixed refineries with large tractor-trailers. Mobile and fixed refineries produce bio-oil from the received biomass. The production rate of bio-oil depends on the percentage yield and the capacity of refineries. Small tanker trucks move bio-oil from mobile refinery sites to warehouses. Large tanker trucks move bio-oil from fixed refinery sites to warehouses. There is a constraint on the capacity of vehicles to transfer material/product and a constraint on the capacity of sites to hold material/product. In addition, each employee must commute from their residence to their job site.

There are three decision variables (called independent variables in statistical terminology) and three objectives (called dependent variables in statistical terminology). Decision variables are mass of biomass to be transported, mass of bio-oil to be transported, and the locations of refineries and warehouses. The optimized values of decision variables are obtained using a multi-objective mathematical model for improving three objectives in this work: total cost, carbon footprint, and number of jobs created.

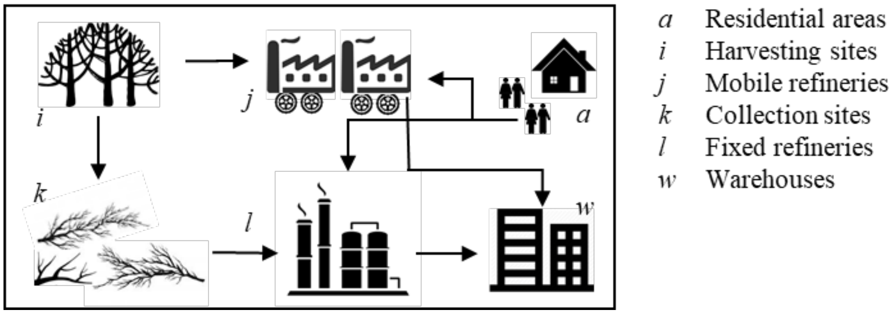

Figure 4.1: The considered biomass to bio oil supply chain

Sustainable Supply Chain Management			
Objective functions	Total cost: Raw material, logistics, facility		
	Carbon dioxide equivalent: Generated by transportation and conversion process		
	The number of jobs created		
Decision variables	Mass of biomass to be transported Mass of bio-oil to be transported The locations of refineries and warehouses		
System	Input: biomass	Conversion processes in refineries	Output: bio-oil
Echelons	Harvesting sites	Mobile refineries	Warehouses
	Collection sites	Fixed refineries	Residential areas
Result	A set of Pareto solutions including the actual cost of bio-oil, carbon footprint generated, and the number of jobs created.		

Figure 4.2: Overview of the problem objectives, approach, and expected results for bio-oil supply chain under study

Since the aim of the proposed multi-objective problem herein is based on a logistics and location approach, a supply side, rather than demand side, situation is formulated in the mathematical model. All of the bio-oil produced is assumed to be sold in the market. Figure 4.2 presents the scheme of the problem presented.

4.3.1 The Mathematical Model

This section presents a multi-objective mathematical model of the bio-oil supply chain introduced above, and uses mixed-integer variables with deterministic parameters. The mathematical notation used for the sets, parameters, variables, and objective functions is presented below.

Sets:

a set of employee residential areas, a=1,…,A,

i set of harvesting sites, i=1,…,I,

j set of mobile refineries, j=1,…,J,

k set of collection sites, k=1,…,K,

l set of fixed refineries, l=1,…,L,

v set of vehicles, v=1,…,V,

w set of warehouse sites, w=1,…,W,

Parameters:

B Capacity; e.g., B_{jt}: storage capacity site j in period t,

b Working capacity of an employee (the number of hours per day),

c Total cost of establishing a location; e.g., c_{kt}: total cost of establishing site k in period t,

$C^{s/l/st/lt}$ Transportation cost for a vehicle (s: small tractor-trailer, l: large tractor-trailer, st: small tanker trailer, and lt: large tanker trailer),

D Distance between sites; e.g., D_{ijt}: distance between site i and site j in period t,

F The lowest level of utilization of woody biomass,

$G^{s/l/st/lt}$ Emission factor for vehicles (kg of carbon dioxide equivalent CO_2e per mile),

G Emission factor (kg CO_2e) per one employee per one mile traveled,

G^B Emission factor for producing bio-oil (kg of CO_2e per ton),

g^l Production capacity of a fixed refinery,

g^j Production capacity of a mobile refinery,

H Number of labor hours required; e.g., H_{lt}: number of labor hours required for producing one ton of biomass at site l in period t,

M Big M (large positive constant),

o Operating cost of a refinery,

O Number of available employees,

p Raw material price,

$Q^{s/l/st/lt}$ Capacity of vehicles

S Percentage yield

Decision Variables:

X Mass of biomass; e.g., X_{klt}: mass of biomass transferred from site k to site l in period t, *Y* Mass of bio-oil; e.g., Y_{lwt}: mass of bio-oil transferred from site *l* to site *w* in period *t*,

z $\begin{cases} 1 & \text{if site is open} \\ 0 & \text{otherwise} \end{cases}$, e.g., $z_{kt} = 1$ if site *k* period *t* is open; otherwise $z_{kt} = 0$,

Dependent Variables:

E Number of fixed employees for each refinery,

N Number of vehicle trips; e.g., N_{ijt}: number of trips from site *i* to site *j* in period *t*,

P Number of employees in each residential area; e.g., P_{alt}: number of employees living in residential area *a* and working at site *l*,

TC Total cost,

TCF The total carbon footprint

PC The predicted cost of bio-oil

Objective Functions: The mathematical model presented herein includes three objective functions: an economic function, an environmental function, and a societal function, which are formulated below.

Economic Function: The economic function is considered by investigating the total cost of the proposed bio-oil supply chain, which consists of raw material cost (*RMC*), transportation cost (*TrC*), and facility location cost (*FLC*).

$$Total\ Cost = RMC + TrC + FLC \tag{4.1}$$

Total raw material cost (*RMC*) is calculated by multiplying the total mass of biomass (*X*) by the unit raw material price (*p*).

$$RMC = p\sum_{t}\sum_{i}\sum_{j}\sum_{k}\left(X_{ijt} + X_{ikt}\right) \tag{4.2}$$

Biomass and bio-oil are transported between five locations (harvesting and collection sites, mobile and fixed refineries, and warehouses) using four types of trucks (small and large tractor-trailers and small and large tanker trucks). Transportation cost (*TrC*) is given as,

$$TrC = TrC\ of\ biomass + TrC\ of\ bio\text{-}oil \tag{4.3}$$

where,

$$TrC\ of\ biomass = \sum_{t}\left(\sum_{i}\sum_{j} D_{ijt}C_{ijt}^{s}N_{ijt} + \sum_{i}\sum_{k} D_{ikt}C_{ikt}^{s}N_{ikt} + \sum_{k}\sum_{l} D_{klt}C_{klt}^{l}N_{klt}\right) \tag{4.3a}$$

$$TrC\ of\ bio\text{-}oil = \sum_{t}\left(\sum_{j}\sum_{w} D_{jwt}C_{jwt}^{st}N_{jwt} + \sum_{l}\sum_{w} D_{lwt}C_{lwt}^{sl}N_{lwt}\right) \tag{4.3b}$$

The first term of Eq. (4.3a) indicates the transportation cost between harvesting sites and mobile refineries, which is the summation of the product of D_{ijt} (the shortest distance between sites), C^{s}_{ijt} (operational cost of a small tractor-trailer), and N_{ijt} (the required number of truck-trips). The number of truck trips is calculated as the mass of biomass or bio-oil divided by truck or tanker capacity, respectively. The other terms are developed in a similar manner.

The facility location cost (*FLC*), shown in Eq. (4.4), focuses on the primary cost drivers. Thus, *FLC* consists of costs such as installation costs and fixed operating and maintenance costs.

$FLC = FLC_a + FLC_b$ (4.4)

where FLC_a represents the fixed costs of operation,

$$FLC_a = \sum_t \left(\sum_k c_{kt} z_{kt} + \sum_l c_{lt} z_{lt} + \sum_j c_{jt} z_{jt} + \sum_w c_{wt} z_{wt} \right) \tag{4.4a}$$

and FLC_b are the variable operating costs,

$$FLC_b = \sum_t \left(\sum_k X_{kt} o_{kt} z_{kt} + \sum_l Y_{lt} o_{lt} z_{lt} + \sum_j Y_{jt} o_{jt} z_{jt} + \sum_w Y_{wt} o_{wt} z_{wt} \right) \tag{4.4b}$$

The first term of Eq. (4.4a) indicates the capital/equipment costs associated with collection sites, calculated as the summation of establishment costs (c_{kt}) for the selected collection sites ($z_{kt} = 1$).

Note that the predicted cost (*PC*) of the final product, bio-oil, is calculated by dividing the total cost (Eq. (4.1)) by the total amount of bio-oil produced.

Environmental Function: The environmental objective is investigated by calculating the total carbon footprint (CF) of the bio-oil supply chain. The total carbon footprint includes employee commuting (Boukherroub et al., 2015), conversion processes (Mirkouei et al., 2016), and transportation activities (Rezaei & Kheirkhah, 2018), and considers the relevant emission factors for each activity. Therefore, the total carbon footprint is calculated as follows (Eq. (4.5)).

Total CF = CF of commuting + CF of conversion processes + CF of transportation (4.5)

The carbon footprint of commuting is Eq. (4.5a),

$$CF\ of\ commuting = G\sum_{t}\left(\sum_{a}\sum_{j}D_{ajt}\times P_{ajt}+\sum_{a}\sum_{l}D_{alt}\times P_{alt}\right) \tag{4.5a}$$

The total CF of commuting is the summation of the product of distance between each employee's home and their assigned work site (*D*), the number of employees at each worksite who commute from their home (*P*), and the carbon emission factor for commuting per one employee per one mile traveled (kg of CO_2e/mile).

The carbon footprint of conversion processes is (Eq. (4.5b)),

$$CF\ of\ conversion\ processes = G^{B}\sum_{t}\sum_{l}\sum_{j}\sum_{w}\left(Y_{lwt}+Y_{jwt}\right) \tag{4.5b}$$

in which the total CF of all conversion processes is the sum of multiplication products of produced bio-oil and the carbon emission factor for producing bio-oil (kg of CO_2e/ton).

The carbon footprint of transportation is (Eq. (4.5c)),

$$CF\ of\ transportation = G^{s}\sum_{t}\left(\sum_{i}\sum_{j}D_{ijt}\times N_{ijt}+\sum_{i}\sum_{k}D_{ikt}\times N_{ikt}\right)+G^{l}\sum_{t}\left(\sum_{k}\sum_{l}D_{klt}\times N_{klt}\right)$$

$$+G^{st}\sum_{t}\left(\sum_{j}\sum_{w}D_{jwt}\times N_{jwt}\right)+G^{lt}\sum_{t}\left(\sum_{l}\sum_{w}D_{lwt}\times N_{lwt}\right) \tag{4.5c}$$

in which, total CF of transportation is the summation of the products of distances between locations (*D*), the number of vehicle trips (*N*), and the carbon emission factor for vehicles (kg of CO_2e /mile).

Societal Function: The research presented herein uses two indicators, local employment (Boukherroub et al., 2015) and the number of jobs created (Pérez-Fortes et al., 2012; Pishvaee, Razmi, & Torabi, 2014; Rezaei & Kheirkhah, 2018), to represent societal functional performance. The proximity of employees living near work sites leads to local employment. Thus, the total distance traveled can be minimized to increase local employment (Boukherroub et al., 2015). Since the carbon footprint of commuting is considered in the environmental function, this objective will be satisfied by minimizing carbon emissions. As shown in Eq. (4.6), the number of jobs created in the bio-oil supply chain is calculated as a summation of the number of fixed and variable employees who work in each refinery,

$$\text{Max Jobs} = \sum_t \sum_a \sum_j \sum_l \left(P_{ajt} + P_{alt} \right) + E \sum_j \sum_l \left(z_j + z_l \right) \tag{4.6}$$

in which the first term indicates the variable employees and the second term shows the fixed employees. The number of jobs created includes several limitations presented in the constraints below.

In general, the three objective functions of the mathematical model are:

Minimize the *Economic Function* shown in Eq. (4.1)

Minimize the *Environmental Function* shown in Eq. (4.5)

Maximize the *Societal Function* shown in Eq. (4.6)

Subject to the following constraints:

$$N_{ijt} = \lceil X_{ijt} / Q^{s} \rceil \qquad \forall_i \in I, \forall_j \in J, \forall_t \in T \qquad \text{(The number of truck trips)} \qquad (4.7)$$

$$N_{ikt} = \lceil X_{ikt} / Q^{s} \rceil \qquad \forall_i \in I, \forall_k \in K, \forall_t \in T \qquad \text{(The number of truck trips)} \qquad (4.8)$$

$$N_{klt} = \lceil X_{klt} / Q^{l} \rceil \qquad \forall_k \in K, \forall_l \in L, \forall_t \in T \qquad \text{(The number of truck trips)} \qquad (4.9)$$

$$N_{jwt} = \lceil Y_{jwt} / Q^{st} \rceil \qquad \forall_j \in J, \forall_w \in W, \forall_t \in T \qquad \text{(The number of truck trips)} \qquad (4.10)$$

$$N_{lwt} = \lceil Y_{lwt} / Q^{lt} \rceil \qquad \forall_l \in L, \forall_w \in W, \forall_t \in T \qquad \text{(The number of truck trips)} \qquad (4.11)$$

$$\sum_i X_{ikt} = \sum_l X_{klt} \qquad \forall_k \in K, \forall_t \in T \qquad \text{(Inputs and outputs)} \qquad (4.12)$$

$$\sum_j Y_{jwt} + \sum_l Y_{lwt} = Y_{wt} \qquad \forall_w \in W, \forall_t \in T \qquad \text{(Inputs and outputs)} \qquad (4.13)$$

$$\sum_i X_{ikt} \leq Mz_{kt} \qquad \forall_k \in K, \forall_t \in T \qquad \text{(Site status: Open or closed)} \qquad (4.14)$$

$$\sum_i X_{ijt} \leq Mz_{jt} \qquad \forall_j \in J, \forall_t \in T \qquad \text{(Site status: Open or closed)} \qquad (4.15)$$

$$\sum_k X_{klt} \leq Mz_{lt} \qquad \forall_l \in L, \forall_t \in T \qquad \text{(Site status: Open or closed)} \qquad (4.16)$$

$$\sum_j Y_{jwt} \leq Mz_{wt} \qquad \forall_w \in W, \forall_t \in T \qquad \text{(Site status: Open or closed)} \qquad (4.17)$$

$$\sum_l Y_{lwt} \leq Mz_{wt} \qquad \forall_w \in W, \forall_t \in T \qquad \text{(Site status: Open or closed)} \qquad (4.18)$$

$$\sum_a P_{ajt} \leq Mz_{jt} \qquad \forall_j \in J, \forall_t \in T \qquad \text{(Site status: Open or closed)} \qquad (4.19)$$

$$\sum_a P_{alt} \le Mz_{lt} \qquad \forall_l \in L, \forall_t \in T \qquad \text{(Site status: Open or closed)} \qquad (4.20)$$

$$\sum_a P_{ajt} = \left\lceil \left(H_{jt} \times \sum_w Y_{jwt} \right) \Big/ b \right\rceil \qquad \forall_j \in J, \forall_t \in T \qquad \text{(The number of employees)} \qquad (4.21)$$

$$\sum_a P_{alt} = \left\lceil \left(H_{lt} \times \sum_w Y_{lwt} \right) \Big/ b \right\rceil \qquad \forall_l \in L, \forall_t \in T \qquad \text{(The number of employees)} \qquad (4.22)$$

$$\sum_j P_{ajt} + \sum_l P_{alt} = O_a \qquad \forall a \in A, \forall t \in T \qquad \text{(Employees available)} \qquad (4.23)$$

$$\sum_i X_{ikt} \le B_{kt} \qquad \forall_k \in K, \forall_t \in T \qquad \text{(Storage capacity for biomass)} \qquad (4.24)$$

$$\sum_i X_{ijt} \le B_{jt} \qquad \forall_j \in J, \forall_t \in T \qquad \text{(Storage capacity for biomass)} \qquad (4.25)$$

$$\sum_k X_{klt} \le B_{lt} \qquad \forall_l \in L, \forall_t \in T \qquad \text{(Storage capacity for biomass)} \qquad (4.26)$$

$$\sum_j Y_{jwt} + \sum_l Y_{lwt} \le B_{wt} \qquad \forall_w \in W, \forall_t \in T \qquad \text{(Storage capacity for bio-oil)} \qquad (4.27)$$

$$Y_{jt} \le g^j \qquad \forall_j \in J, \forall_t \in T \qquad \text{(Production capacity for bio-oil)} \qquad (4.28)$$

$$Y_{lt} \le g^l \qquad \forall_l \in L, \forall_t \in T \qquad \text{(Production capacity for bio-oil)} \qquad (4.29)$$

$$S \times \sum_i X_{ijt} = \sum_w Y_{jwt} \qquad \forall_j \in J, \forall_t \in T \qquad \text{(Biomass converted to bio-oil)} \qquad (4.30)$$

$$S \times \sum_k X_{klt} = \sum_w Y_{lwt} \qquad \forall_l \in L, \forall_t \in T \qquad \text{(Biomass converted to bio-oil)} \qquad (4.31)$$

$$\sum_i \left(\sum_j X_{ijt} + \sum_k X_{ikt} \right) \geq F \qquad \forall_t \in T \qquad \text{(Available woody biomass)} \qquad (4.32)$$

$$X_{ijt}, X_{ikt}, X_{klt}, Y_{jwt}, Y_{lwt} \geq 0 \qquad \text{(Continuous decision variables)} \qquad (4.33)$$

$$N_{ijt}, N_{ikt}, N_{klt}, N_{jwt}, N_{lwt} \geq 0, \text{int} \qquad \text{(Integer decision variables)} \qquad (4.34)$$

$$z_{jt}, z_{kt}, z_{lt}, z_{wt} = \begin{cases} 1 & \text{if location is open,} \\ 0 & \text{otherwise.} \end{cases} \qquad \text{(Binary decision variables)} \qquad (4.35)$$

$$P_{ajt}, P_{alt} \geq 0, \text{ int} \qquad \text{(Integer decision variables)} \qquad (4.36)$$

The number of vehicle trips is calculated by rounding up the amount of transferred product and dividing by vehicle capacity, as shown in Eqs. (4.7-4.11). As there are four types of vehicles, four types of vehicle trips are provided. Eq. (4.12) guarantees that the input and output masses of biomass at the collection sites are equal. Similarly, Eq. (4.13) shows that the total mass of bio-oil produced by the refineries is equal to the mass of stored bio-oil in warehouses. Eqs. (4.14-4.18) indicate the site status (open or closed); materials will be sent only to those sites that are open (working). Similarly, as shown in Eqs. (4.19-4.20), employees commute to those refineries that are open (working). Eq. (4.21) shows the number of employees who work at mobile refinery *j*. The number of employees is calculated by dividing the number of person-hours required to produce bio-oil in a refinery by an employee’s working capacity. The person-hours required to produce bio-oil in a refinery is calculated by multiplying a person-hour factor per ton of bio-oil (*H*) by the mass of bio-oil produced in a refinery. Each employee has a working capacity (*b*), (e.g., 8 hours per day). Eq. (4.22) calculates the total number of employees working at fixed refineries. The number of employees living in residential area (city) *a* during period *t*, is equal to the number of employees working in mobile and fixed refineries during period *t* that are served by city *a*. In other words, the number of employees hired from a given region should not exceed the total number of potential employees available in that region, which is presented in Eq. (4.23). Eqs. (4.24-4.27) indicate the storage capacity for collection sites, mobile refineries, fixed refineries, and warehouses, respectively. Eqs. (4.28-4.29) represent the production capacity of mobile and fixed refineries, respectively. The biomass is converted to bio-oil by the refineries with some losses, as captured by a percentage yield parameter *S*. Eq. (4.30) calculates the amount of bio-oil produced in mobile refineries, and similarly, Eq. (4.31) calculates the amount of bio-oil produced in fixed refineries. Eq. (4.32) enforces refineries (mobile, fixed, or both) to consume all the available woody biomass at harvesting and collection sites. The decision variables are defined in Eqs. (4.33-4.36). In the next section, the mathematical model is further developed using a demonstration for a representative biomass to bioenergy supply chain in the northwestern United States.

4.4 Application of the Model

The foregoing mathematical model is developed for optimizing the sustainability performance of a biomass to bio-oil supply chain utilizing a mix of fixed and mobile refineries and a heterogeneous fleet. The multi-objective optimization problem considers total cost, carbon footprint, and number of jobs created. To demonstrate the application of the model, actual data (e.g., biomass availability and cost, unemployment rate, and vehicle fuel consumption) is derived from research literature and governmental reports. Costs are adjusted for inflation to 2017.

The raw material is woody biomass, which is \$25/ton (U.S. EPA, 2017), and the final product is bio-oil with an estimated price interval of between \$0.78/gal. and \$1.76/gal. Based on reported values for 2013-2016 (Mirkouei et al., 2017). The considered bio-oil has an approximate density of 10 lb./gal. at 59 °F (1.20 kg/L at 15 °C) with higher heating value energy content of approximately 18 MJ/kg (Steele, Puettmann, Penmetsa, & Cooper, 2012). The research presented here considers four counties in northwest Oregon: Clatsop, Columbia, Tillamook, and Washington, which are assumed to have 11.5, 6.1, 13.2, and 6.1 millions of bone dry tons (BDT) of net biomass available, respectively, based on 2002 data (Technical Report by Oregon State University, 2017). As seen in Figure 4.3, which shows US Forest Service data from May 2017 (Arcgis, 2017), northwest Oregon is part of one of the highest producing regions of woody biomass in the US (U.S. Forest Service, 2017).

In this demonstration, forty-three harvesting sites, nine collection sites, seven mobile refineries, four fixed refineries, and four warehouses are selected as potential locations. Potential locations near main roads are selected using ArcGIS software (version 10.5.1) with regard to databases provided by the US Forest Service, Oregon Department of Transportation, and State of Oregon Geospatial Enterprise Office. Potential refinery sites are located in flat treeless zones to mitigate in-forest bio-oil transportation challenges. Four cities, Astoria, St. Helens, Tillamook, and Portland, are considered as employee residential areas.

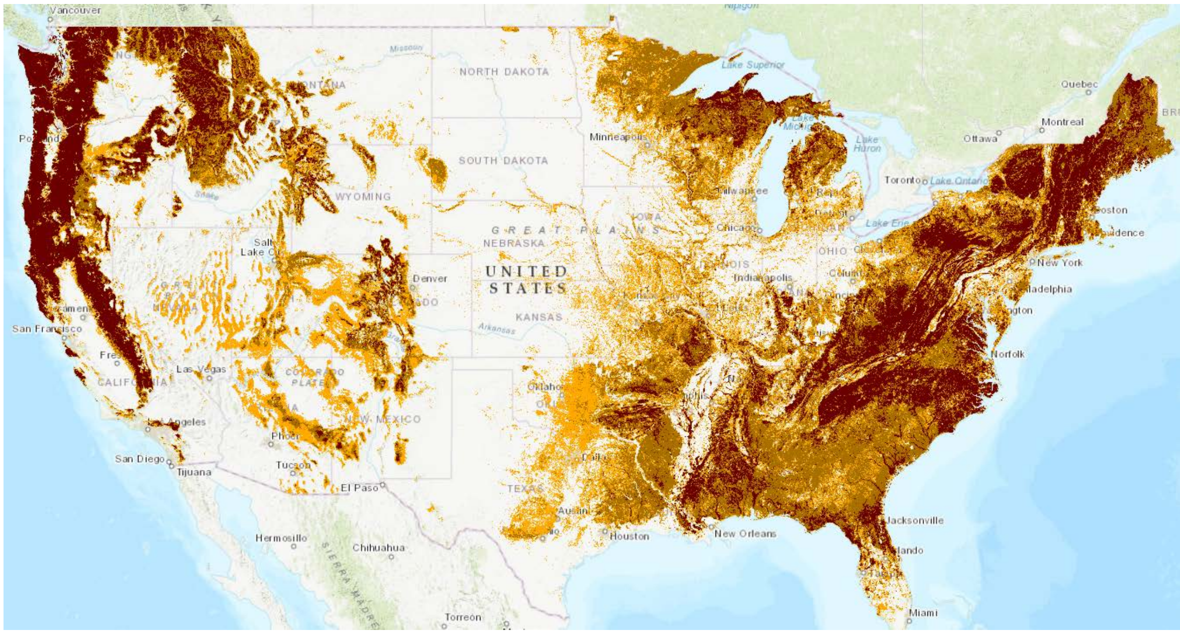

Figure 4.3: The distribution of woody biomass across the contiguous US (ArcGIS, 2017)

Potential existing warehouses in Oregon are selected based on the storage cost and the distance to mobile and fixed refineries. Since warehouses are assumed to be provided by a third party, storage costs include employee costs and all other costs related to warehousing. In addition to their location, two other warehouse characteristics ─ capacity and rental rate ─ are needed to develop the proposed model.

The number of available employees is calculated using the average U.S. unemployment rate for 2017 (4.14% (U.S. Bureau of Labor Statistics, 2018b)) and population in each city given by the 2010 census (U.S. Department of Commerce, 2010). It is assumed that employees have the required skills for the positions. The classification of employee type is left for future research. The number of fixed employees in each refinery is assumed to be nine people (Mullaney, Farag, LaClaire, & Barrett, 2002). The person-hour factor for producing one ton of bio-oil is 0.218 person-hours per ton-year (Mullaney et al., 2002). The employee's work capacity is assumed to be eight hours per day. Thus, for three work shifts, the person-year factor for producing one ton of bio-oil is 0.027 persons per ton-year.

The cradle-to-grave environmental impact of producing bio-oil, which includes collection and pyrolysis of biomass, is 0.0323 kg of CO_2e per MJ of bio-oil (Mirkouei et al., 2016). The carbon equivalent emission factor for a 12-passenger van (for commuting) is 0.485 of CO_2e kg/vehicle-mile (U.S. EPA, 2015). The emission factor for a medium/heavy-duty truck is 0.146 CO_2e kg/ton-mile. These emissions factors are assumed to hold for loaded and unloaded vehicles.

The capacity of a wheel-mounted mobile refinery is 1,650 thousand liters per year (Mirkouei et al., 2016). Fixed refineries have a capacity of 43,930 thousand liters per year. The total cost of establishing a refinery includes fixed cost (capital cost divided expected life-years) and variable cost per ton of bio-oil produced (Mirkouei et al., 2016). These costs include insurance, utilities, maintenance, taxes, and chemicals. To avoid inventory cost, a just-in-time approach is assumed for the production of bio-oil and the flow of biomass in the bio-oil supply chain. The total truck transportation cost is $4.98 ton/hour, adjusting for inflation to 2017, based on the value presented by Mason et al. (2008).

4.5 Results and Sensitivity Analysis

This section shows how the mathematical model presented herein can be used as a decision support tool. The data described in the previous section is applied in the model developed using IBM ILOG CPLEX 12.7.1 software on a Windows 10 64-bit Operation System with

Intel Core i5 processor (CPU 3.40GHz) and 16GB RAM.

The objectives are normalized and then the weighted goal programming technique (Boukherroub et al., 2015) is employed to generate a set of optimal Pareto solutions. The Pareto-efficient frontier illustrates the different tradeoffs between the societal, environmental, and economic objectives.

Before using the weighting method, the three objectives in the proposed model are normalized, since each objective has a different value scale. For example, the number of employees required in a bio-oil supply chain might range from 10 to 1000, while the total cost would be on the order of a million dollars. The objectives are normalized by dividing the value of each objective (Z) by the best value for each objective (Z^*). To obtain the best value for each objective, each is optimized without considering the other two objectives. The maximization function (Z_3) is changed to a minimization function as shown in Eq. (4.37).

$$\begin{matrix} Min\ \{Z_1\} \\ Min\ \{Z_2\} \\ Max\ \{Z_3\} \end{matrix} \quad \Rightarrow Min\left\{ w_1 \frac{Z_1}{Z_1^*} + w_2 \frac{Z_2}{Z_2^*} - w_3 \frac{Z_3}{Z_3^*} \right\}; \tag{4.37}$$

Also, as shown in Eq. (4.37), after normalizing the objectives, we merge the three objectives into a single objective by using weighting factors w. Note that the sum of the three weights is equal to one. To provide the Pareto optimal solutions, decision makers can vary the weights.

CPLEX solves the problem with 1,045 constraints and 1,690 variables after 10,577 iterations. Table 4.1 shows each optimized objective obtained without considering other the two objectives. The first column represents the optimal solution based on the economic aspect while the second and the third columns present the optimal solutions based on the environmental and societal aspects, respectively. The first column presents a solution requiring three mobile refineries and one warehouse, in which the actual cost of bio-oil is predicted to be $1.34/gal ($0.35/L). This cost falls in the cost interval found in the market and research literature (between $0.78/gal and $1.76/gal (Mirkouei et al., 2017)). The related supply chain would require ninety employees to produce 2,306,250 liters of bio-oil, while the supply chain activities would add 5,369 kg CO_2e of emissions into the environment. These emissions would consist of 175 kg, 1,609 kg, and 3,585 kg CO_2e of emissions due to commuting, conversion processes, and logistics activities, respectively.

Table 4.1: Three optimal solutions based on individually weighting three aspects: economic, environment, and society

Weighting*:	(1,0,0)	(0,1,0)	(0,0,1)
Objective:	Min. Total Cost	Min. Carbon Footprint	Max. jobs created
Economic	<u>$819,756</u>	$5,586,835	$7,476,347
Environmental	5,369 kg CO_2e	<u>3,507 kg CO_2e</u>	46,699 kg CO_2e
Societal	90	126	<u>347</u>
Cost of bio-oil	<u>$1.34/gal</u>	$9.17/gal	$3.11/gal

* The parenthetical indicates weighting factors for economic, environmental, and societal objectives, respectively.

In Table 4.1, each column provides the best value (underlined), based on each objective. For example, the first column is optimized based on the economic aspect and represents the lowest total cost ($816,756), which is significantly lower than that for minimizing carbon footprint ($5,586,835) and maximizing the number of jobs created ($7,476,347).

Similarly, the second column represents the solution with the lowest carbon footprint (3,507 kg CO_2e), compared to 5,369 kg CO_2e (lowest cost) and 46,699 kg CO_2e (most jobs created). The third column represents a solution with the most jobs created (347 person-years), compared to 90 person-years (lowest cost) and 126 person-years (lowest carbon footprint).

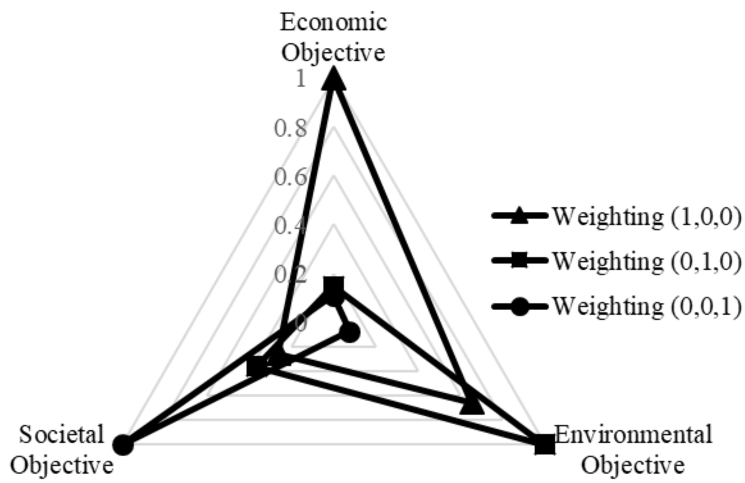

Figure 4.4: Optimized values for normalized objectives based on Table 4.1

Figure 4.4 presents a radar graph for the three optimal normalized solutions presented in Table 4.1. Each triangle indicates the normalized values of the three indicators for the related optimal solution, where the optimized objective is reported to have a normalized value of one. As shown in Figure 4.4, the three optimal solutions (each triangle) are non-dominated. A solution is non-dominated if it outperforms the other solution sets for any indicator. All near-optimal solutions, provided by varying weights, must be non-dominated in the set of optimal solutions that will be used by the decision maker. This is shown in Figure 4.5 for a hypothetical example, which shows one dominated solution in a set of three feasible solutions, i.e., the smaller triangle, shown with circular vertices is dominated by the other two solutions in each category. This smaller triangle is dominated by the larger triangle shown with triangular vertices, and will be removed from the set of solutions.

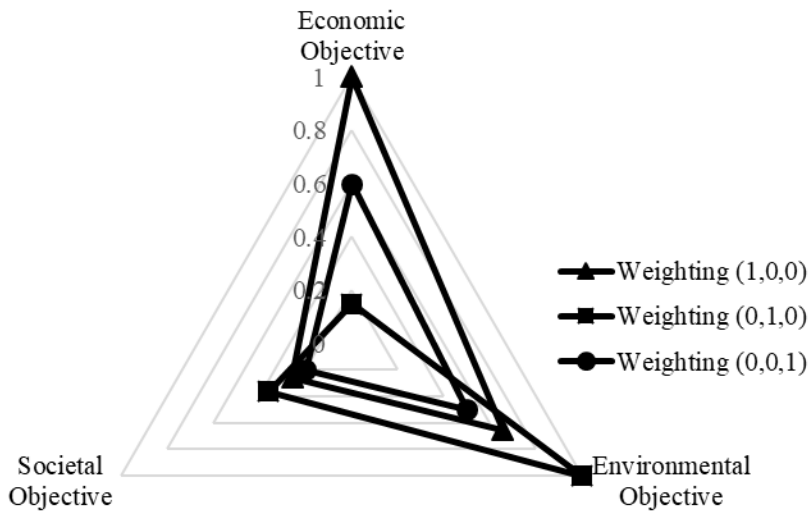

Figure 4.5: A dominated optimal solution (indicated with circles at the vertices)

The results of the bio-oil supply chain presented herein were compared with those for a traditional supply chain using only fixed refineries. As shown in Table 4.2, use of mobile refineries are predicted to reduce the cost of bio-oil (decreasing from \$4.48/gal to \$1.34/gal). By taking into account the predicted cost of bio-oil, it can be see that incorporating mobile refineries would give bio-oil supply chains a distinct advantage over traditional supply chains using only fixed refineries. Use of mobile refineries also reduces the commuting-related carbon footprint, while the emissions due to conversion processes remain the same. Since fixed refineries use larger tanker trucks and require fewer trips to transport bio-oil to warehouses, the transportation carbon footprint in the traditional supply chain is less than in the mixed bio-oil supply chain. Both supply chains are predicted to create the same number of jobs.

Table 4.2: Comparison between traditional and mixed bio-oil supply chain

Variables	Mixed bio-oil supply chain including mobile and fixed refineries	Bio-oil supply chain including fixed refineries
Cost of bio-oil	\$1.34/gal	\$4.48/gal
CF* of commuting	175 kg CO_2e	271 kg CO_2e
CF of conversion processes	1609 kg CO_2e	1609 kg CO_2e
CF of transportation	3585 kg CO_2e	2009 kg CO_2e
The number of jobs created	90 people	90 people

*CF = Carbon footprint

4.5.1 Sensitivity Analysis

The bio-oil supply chain parameters impact the model dependent variables. This section considers the effect of five parameters on economic, environmental, and societal performance by running 32 scenarios. The five parameters studied include mobile refinery capital cost, refinery operating cost, total available woody biomass, mobile refinery storage capacity, and percentage yield. Increasing and decreasing values scenarios are considered for each parameter, which are then compared with the base scenario with regard to total cost, carbon footprint, and the number of jobs created. The following sections discuss the sensitivity analysis of each of the parameters. Note that objectives have the same weighting factor (1/3) in all cases considered, and the value of variables for the base case are shown in Table 4.3.

Table 4.3: The values of model outputs for the base case with equal weighting of objectives (0.33, 0.33, 0.33)

Model Output	Value
Total cost ($)	868,140
Total carbon footprint (kg CO_2e)	4,239
The number of jobs created (people)	90
Predicted cost of bio-oil ($/gal.)	1.42
Total facility location cost ($)	719,070
Total transportation cost ($)	33,760
Total carbon footprint of commuting (kg CO_2e)	114
Total carbon footprint of conversion processes (kg CO2e)	1,609
Total carbon footprint of transportation (kg CO_2e)	2,516
The number of truck trips	459
Total biomass available (ton)	4,613
Number of active mobile refineries	3
Number of active fixed refineries	0
Number of active collection sites	0
Number of active warehouses	1

4.5.1.1 Effect of Mobile Refinery Capital Cost

Six scenarios for the parameter of mobile refinery capital cost are investigated to consider its effect on the performance of the proposed bio-oil supply chain. In the first three scenarios, the mobile refinery capital cost is increased by 10%, 20%, and 30%. In the second three scenarios, the mobile refinery capital cost is decreased by 10%, 20%, and 30%. In all six scenarios, three variables, facility location cost, total cost, and predicted cost of bio-oil, are affected. Figure 4.6 illustrates a positive linear relationship exists between mobile refinery capital cost and the three objectives considered. It can be seen that a 30% increase in mobile refinery capital cost causes an increase in facility location cost of 21%. The total supply chain cost and, consequently, the cost of bio-oil increase by 17%.

The sensitivity analysis found that mobile refinery capital cost impacts total cost, while the two other objectives (carbon footprint and number of jobs created) remain unchanged compared to the base scenario. Therefore, as expected, optimizing the mobile refinery capital cost by improving technological performance would allow bio-oil supply chains to reduce the cost of bio-oil.

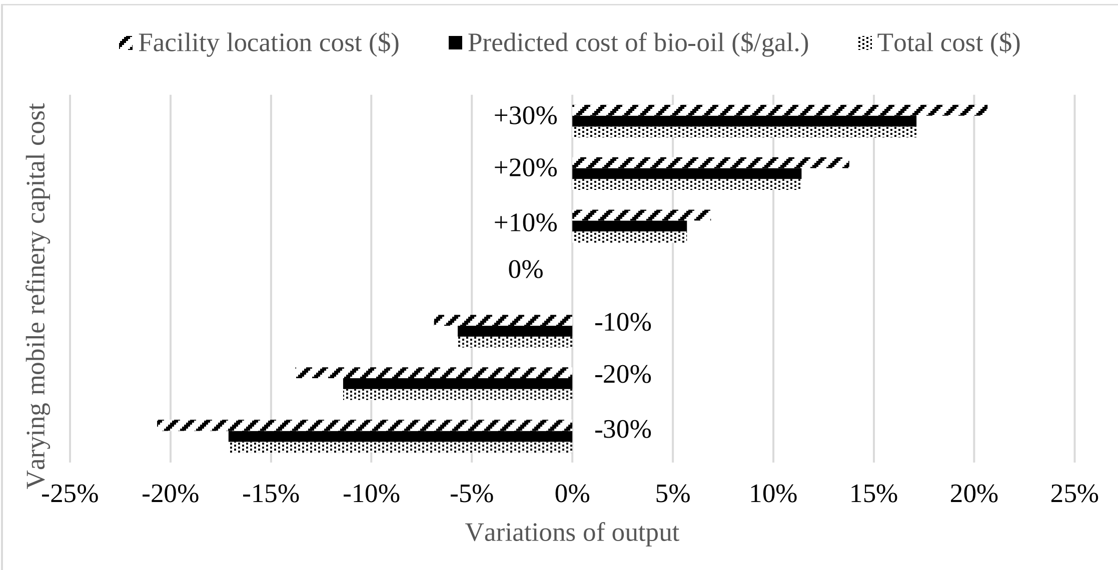

Figure 4.6: Effect of mobile refinery capital cost on costs for the proposed bio-oil supply chain

4.5.1.2 Effect of Operating Cost

Six scenarios are used to evaluate the effect of operating cost on the considered objectives for the proposed bio-oil supply chain. Operating cost impacts the same variables considered in evaluating the effect of mobile refinery capital cost (i.e., facility location cost, total cost, and predicted cost of bio-oil). Values for all three objectives increase linearly with an increase in operating cost. However, this effect is not significant. For example, when operating cost increases by 30% (Figure 4.7), the predicted cost of bio-oil increases by only 4% ($1.42/gal to $1.47/gal). As predicted for increases in mobile refinery cost, when varying operating cost the carbon footprint and the number of jobs created would remain unchanged compared to the base case.

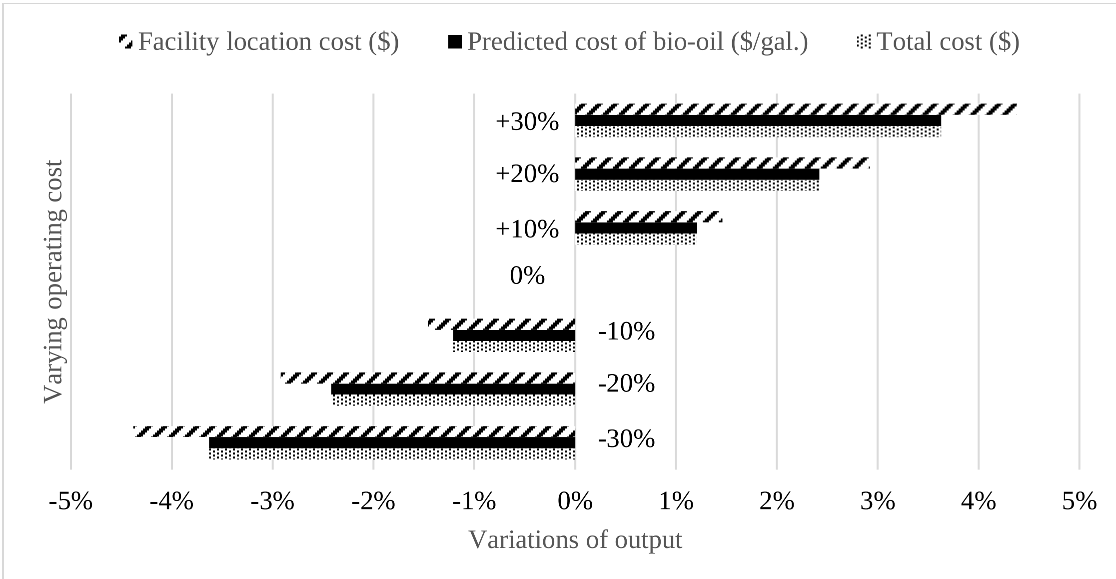

Figure 4.7: Effect of operating cost on the proposed bio-oil supply chain

4.5.1.3 Effect of Percentage Yield

Figure 4.8 demonstrates the behavior of the three selected objectives – total cost, carbon footprint, and number of jobs created – when the percentage yield varies from a decrease of 30% to an increase of 30%. All three objectives increase when the percentage yield is improved. The improvement in percentage yield leads to more bio-oil production, necessitating additional logistics activities and increasing the number of jobs created. In addition, the increase in logistics activities leads to increase in transportation-related carbon emissions. Improving the percentage yield has the effect of reducing the predicted cost of bio-oil. For example, a 30% improvement in percentage yield increases total cost by 4% and leads to 30% more bio-oil. Thus, the overall effect is that the unit cost of bio-oil drops by 20%. This demonstrates a crucial point: both economic and societal aspects will be improved by increasing bio-oil conversion process yields.

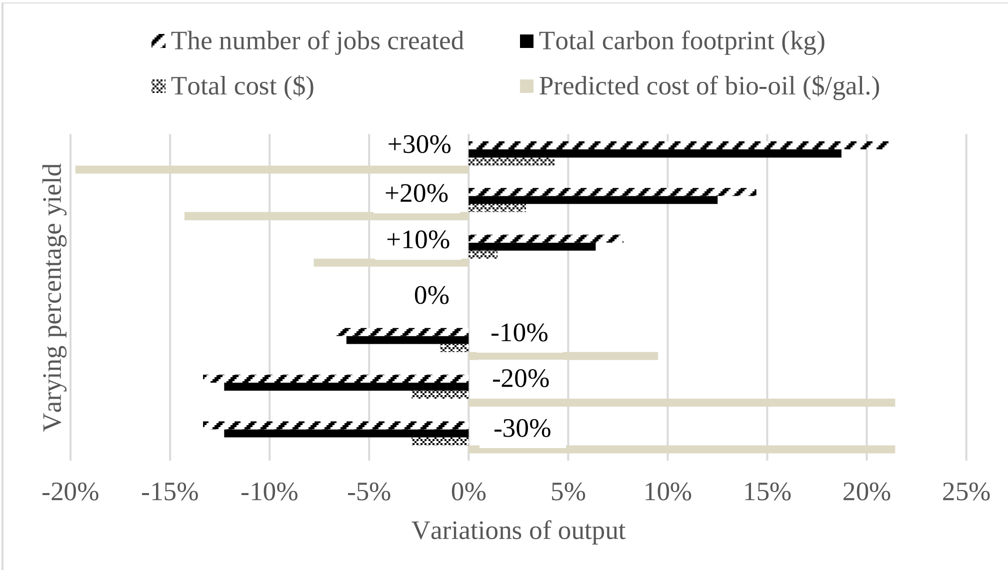

Figure 4.8: Effect of percentage yield on the objective functions

4.5.1.4 Effect of Storage Capacity of Mobile Refinery

The capacity of storage available at mobile refinery locations is a key parameter impacting total cost. Optimizing biomass and bio-oil storage capacity to minimize total cost could have the effect of reducing the number of refineries required to achieve the same output. To evaluate the effect of mobile refinery capacity on the selected bio-oil supply chain, seven scenarios were created. As shown in Figure 4.9, decreasing storage capacity by 10% increases the number of active mobile refineries from three to four. Conversely, when storage capacity is increased by 40%, the number of active mobile refineries decreases from three to two. These changes also impact other bio-oil supply chain objectives, as shown in Figure 4.10. For example, a 40% increase in storage capacity reduces the number of jobs created (10%), increases the total carbon footprint (9%), and reduces the predicted cost of bio-oil (19%). Since fewer active mobile refineries are required, fewer refinery workers are needed. Although reducing bio-oil and biomass storage capacity at mobile refinery locations improves societal aspects by increasing the number of jobs created, it has a significant negative effect on the environment and economy by increasing the carbon footprint and predicted cost of bio-oil, respectively. Increasing storage capacity by 40% leads to a reduction in the predicted cost of bio-oil by 18% (from \$1.42/gal to \$1.16/gal).

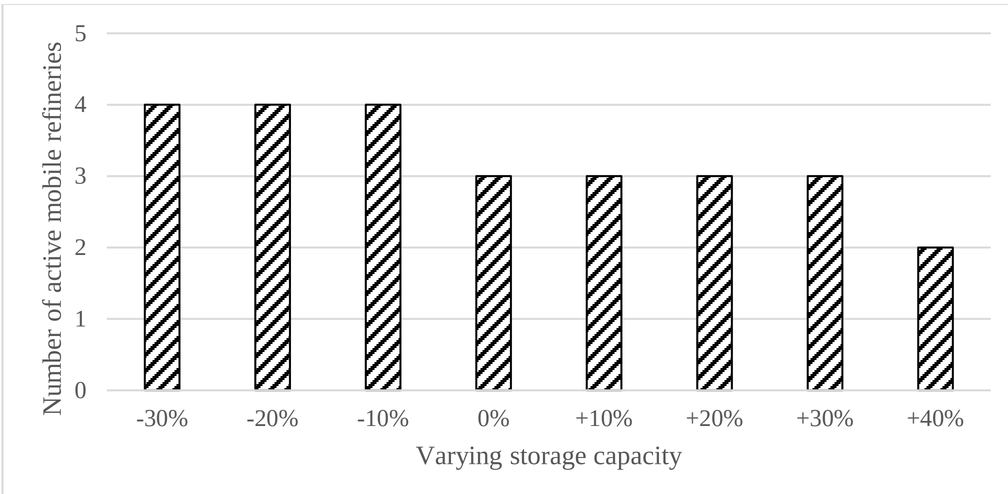

Figure 4.9: Effect of capacity of mobile refinery storage on the number of active mobile refineries

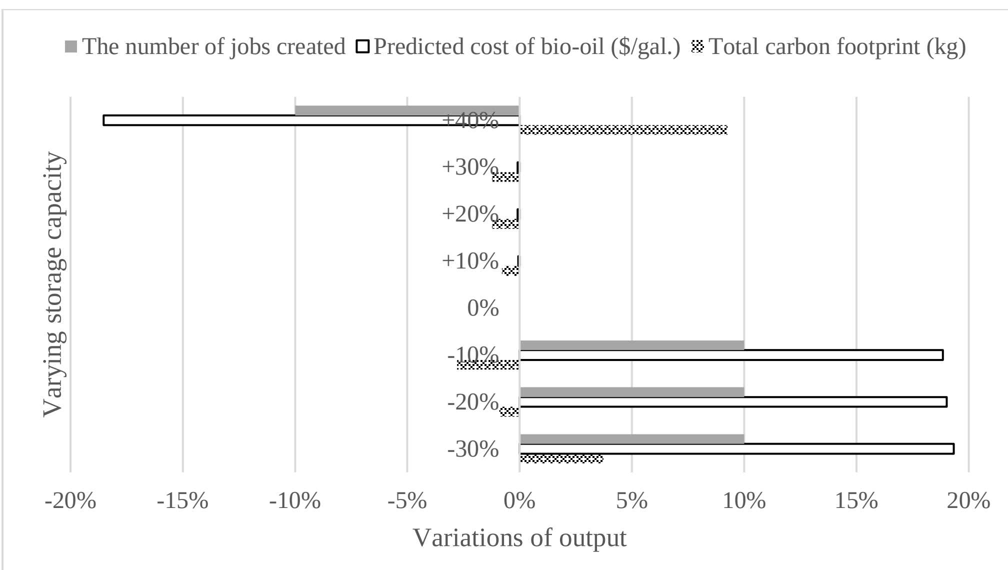

Figure 4.10: Effect of mobile refinery capacity on output variables

4.5.1.5 Effect of Available Woody Biomass

The effect of available woody biomass on the bio-oil supply chain is evaluated using seven scenarios. As shown in Figure 4.11, all three objectives increase fairly linearly with increases in the available woody biomass. While increasing available woody biomass increases the total cost, bio-oil production is increased, decreasing the predicted unit cost of bio-oil. In Figure 4.11, the number of jobs created increases by 38.8% (from 90 to 125 people) when the available woody biomass is increased 40%. Meanwhile, the predicted cost of bio-oil would decrease from $1.42/gal to $1.33/gal (6%). Due to the increase in the number of active mobile refineries, the carbon footprint increases by 43% when the available woody biomass is increased by 40% (see Figure 4.12). Overall, it appears that increasing available woody biomass has a positive impacts society and the economy, while it a negatively effects the environment, when only considering production-related carbon emissions.

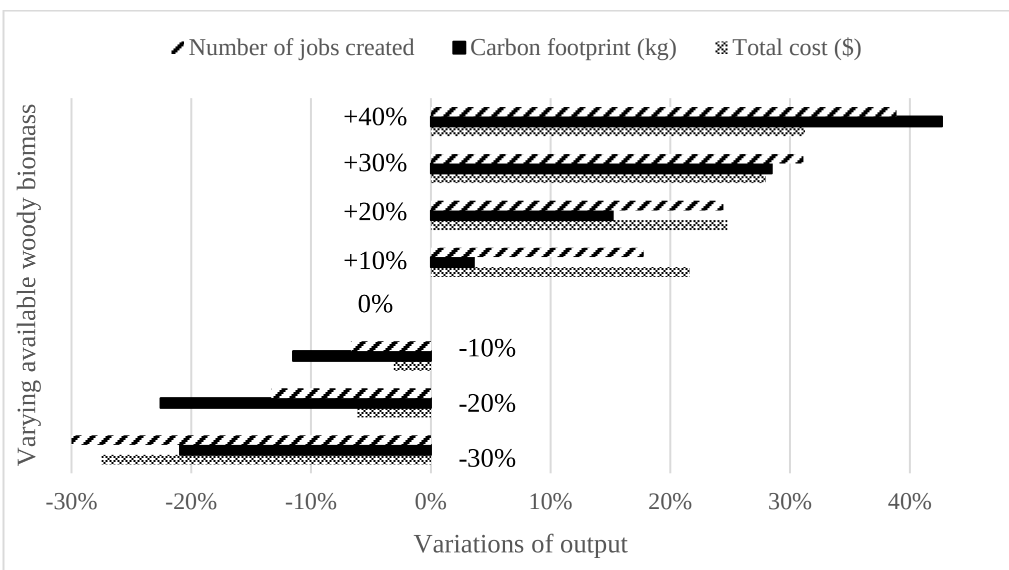

Figure 4.11: Effect of available woody biomass on the objective functions

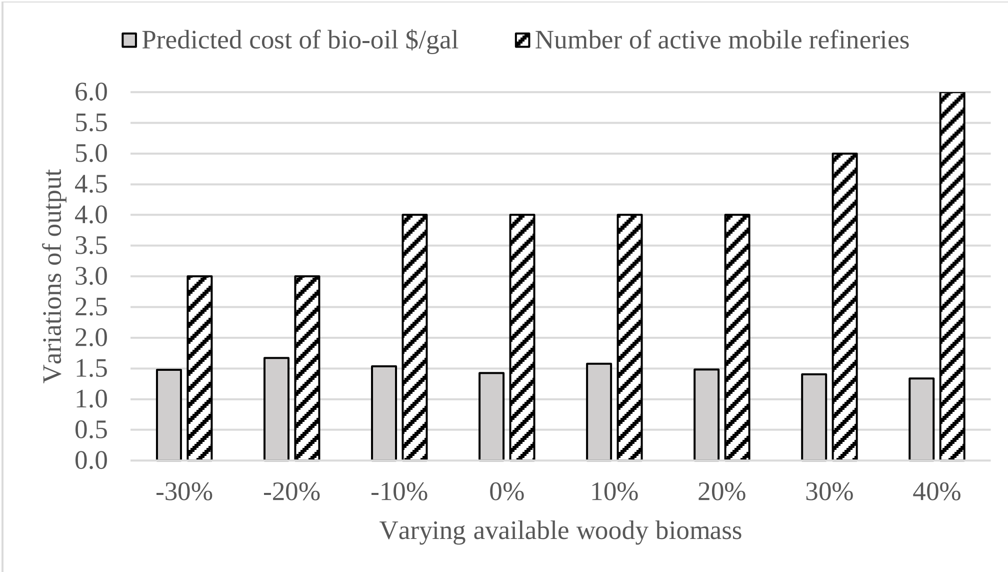

Figure 4.12: Effect of available woody biomass on the output variables

Note that the net effects of bio-oil production on environment (e.g., considering fossil fuel savings) is left for future research.

4.6 Conclusion

Forest management practices and climate change have been attributed to the recent lengthening of wildfire seasons across the globe. Collection of combustible forest biomass for generating renewable energy sources, such as bio-oil, can potentially mitigate wildfire risks. In addition, development of renewable energy industries can aid economic development through job creation, while bioenergy sources can benefit the environment by reducing net carbon emissions. However, the cost of bioenergy today is not competitive with conventional energy, which limits its development and adoption. Further, land managers are unable to make robust decisions due to the existence of many uncertainties, including energy and construction market fluctuations, changes in governmental policies, and weather and climate variation.

The research presented herein developed a three objective mathematical model of a mobile-facility supply chain in which bio oil is produced from woody forest biomass. The three pillars of sustainability, i.e., the economy, environment, and society, were modeled as three independent objectives: total cost, total carbon footprint, and number of jobs created, respectively. Data collected from research literature and governmental reports was used in the mathematical model to estimate the objectives. The weighted goal programming technique was employed for solving the mathematical model to find the set of Pareto solutions.

The model-predicted cost of bio-oil fell within a cost interval found in the market and research literature. The comparison of a mobile-facility supply chain with a traditional bio-oil supply chain using only fixed refineries showed that mobile refineries can significantly reduce the cost of bio oil (from $4.475/gal to $1.34/gal). Therefore, mobile refineries could give bio-oil supply chains a distinct economic advantage. Moreover, the sensitivity analysis of five main model parameters was performed by using 32 scenarios to investigate their effects on the objectives. The results showed that changes in the percentage yield and mobile refinery capacity had a greater effect on the selected objectives than the other parameters tested. It was found that increasing the percentage yield by 10-30% reduces the predicted cost of bio-oil and the number of jobs created by 7-20% and 8-21%, respectively. Moreover, increasing mobile refinery capacity by 10-40% leads to a reduction in the predicted cost of bio-oil (up to 19% from $1.42/gal to $1.16/gal).

The proposed mathematical model enables us to make decisions in bio-oil supply chains using a mix of mobile and fixed facilities to improve various sustainability performance metrics. The model presented reduces the focus on monetary costs in bio oil mobile-facility supply chains such that decision makers can trade between economic, environmental, and societal factors, simultaneously. In the application of the model explored, it is shown that in addition to reducing wildfire risks and energy dependence by collecting combustible forest biomass, consideration of societal aspects in bio-oil supply chains can provide a competitive cost of bio-oil.

The focus of this work was developing a multi-objective mathematical model in a bio-oil supply chain with mobile facilities regarding sustainability criteria. While a majority of the research and modeling efforts for bio-oil supply chains has considered fixed facilities, using mobile refineries, has received little attention. Exploration of mobile refineries is a focus here to elucidate bio-oil supply chain sustainability performance through multi-objective mathematical modeling, and has not been previously reported in literature.

In closing, it should be noted that the mathematical model presented considered societal effects using two indicators: the number of jobs created and the local employment. To more clearly indicate the societal aspects of supply chain sustainability performance, other metrics should be considered in future research. Appropriate societal metrics can be defined and quantified in support of measuring and managing bioenergy supply chain efforts. For example, the United Nations has defined "proportion of people under 25 without employment" in support of its sustainable development goal to "promote sustained, inclusive and sustainable economic growth and decent work for all."

CHAPTER 5: SUMMARY AND CONCLUSIONS

5.1 Summary

More than 500,000 acres of forests burned in Oregon in 2017, presumed to be due to changes in climate and forest management practices. Increasing the collection of dying and dead woody biomass from forests could help reduce fire hazards. The work focuses on using sustainability criteria to develop mathematical models of bio-oil supply chains with mobile facilities. Academic studies and industrial practices for improving supply chain sustainability performance are on the rise as policies and regulations continue to emerge, and as demand for sustainable products continues to grow. Thus, the bioenergy production industry is beginning to make decisions informed by sustainability principles. To make better logistics network and bio-oil supplier decisions in this regard, managers will benefit from developing supply chain problems to include sustainability criteria. The work presented herein developed two mathematical models for supply chains in which combustible forest biomass can be collected and removed to generate renewable energy, such as bio-oil (Madrigal et al., 2017).

In addition to decreasing fire hazards, value creation from underutilized woody forest biomass benefits the environment, society, and economy in other ways (Hubbard et al., 2007). In Chapter 3, for example, a single-objective mathematical modeling approach was presented for optimizing the total cost of a bio-oil supply chain. The mathematical model was based on a multi-echelon supply chain with five levels comprised of harvesting sites, collection sites, mobile refineries, fixed refineries, and warehouses. A genetic algorithm was designed to find an optimized solution for the proposed mixed integer linear programming problem.

In Chapter 4, the mathematical model was developed into a multi-objective problem based on data collected from northwest Oregon forests to simultaneously improve the economic, environmental, and social performance of bioenergy supply chains. The effect of bio-oil supply chain parameters on the three pillars of sustainability (by considering total cost, carbon footprint, number of jobs created) was considered by performing 32 scenarios.

5.2 Conclusions

The mathematical models developed and demonstrated in this research were able to quantify and aggregate sustainability performance metrics for bio-oil supply chains across economic, environmental, and social aspects. The results from Chapter 3 showed that decision makers will be able to select the optimal number of mobile and fixed refineries with regard to total cost. In this case total cost consists of logistics cost and carbon cost, which was obtained using the mathematical model optimized by a genetic algorithm (GA). The GA can be applied for large scale problems to overcome restrictions of exact methods.

As shown in Chapter 4, the application of the mathematical model developed was able to quantify the selected economic, environmental, and social metrics associated with bio-oil supply chains. It was found that the predicted cost of bio-oil was in the interval of bio-oil prices reported by the market and literature. In comparing the bio-oil supply chain proposed in this work with traditional bio-oil supply chains using only fixed refineries, it was found that mobile refineries could significantly reduce the cost of bio-oil. Thus, mobile refineries can give bio-oil supply chains a distinct cost advantage over traditional supply chains.

Further, the results given by sensitivity analysis of five key parameters (mobile refinery capital cost, refinery operating cost, total available woody biomass, mobile refinery storage capacity, and percentage yield) showed that percentage yield and mobile refinery capacity were the two parameters that had the greatest effect on the selected objectives. Increasing percentage yield was found to improve both economic and social aspects by reducing the cost of bio-oil and increasing the number of jobs created, respectively.

In addition to reducing wildfire risks and energy dependence by collecting combustible forest biomass, the research found that consideration of societal aspects in bio-oil supply chains can provide a competitive cost of bio-oil. This result is a direct response to critiques of the theory of sustainability, which claim that capitalistic practices in sustainability cannot be challenged.

5.3 Motivations and Contributions

The research presented herein uses a case study focusing on forests in northwest Oregon. There are three issues of focus in this study: 1) Environmental issues: In 2017, more than five million acres of forests burned in the US (Pierre-Louis, 2017), with a half million alone burning in Oregon; 2) Social issues: In terms of unemployment, Oregon is ranked 27th, and has an unemployment rate of 2% higher than the national average (U.S. Bureau of Labor Statistics, 2018a). Oregon’s unemployment rate impacts both its public education (ranked 38rd (Hammond, 2016)) and personal safety (ranked 39th (Bernardo, 2017)); and 3) Economic issues: Oregon’s GDP (gross domestic product) is ranked 25th in the US (U.S. Department of Commerce, 2018). In addition, $340 million was spent to deal with 2017 forest fires (Loew, 2017). Bio-oil production can benefit environment, society, and the economy (Hubbard, Biles, Mayfield, & Ashton, 2007). For example, bio-oil production can reduce wildfire risks by collecting combustible forest biomass (Madrigal et al., 2017). In addition to the economic growth, bio-oil production can reduce the unemployment rate by creating jobs.

The focus of this work is developing a multi-objective mathematical model in a bio-oil supply chain with mobile facilities regarding sustainability criteria. A majority of the research and modeling efforts for bio-oil supply chains is considering fixed facilities, while using mobile facilities, e.g., mobile refineries, has received little attention. Research for developing a multi-objective mathematical model for bio-oil supply chains with mobile facilities to measure sustainability performance has not yet been reported in literature.

In addition to unavailable studies in the literature to design a genetic algorithm for solving mobile refinery problems with carbon cost included in the total cost, previous mathematical models in bio-oil supply chains with mobile-refineries were unable to answer the research question posed in Section 2.2 with regard to four aspects: 1) The number of jobs created has not been considered as a variable for decision makers; 2) Carbon footprint has not been optimized as a variable in mixed-refinery bio-oil supply chains; 3) Operating costs per product have not been considered in mixed bio-oil problems; and 4) Multiple objectives (e.g., total cost, carbon footprint, and the number of jobs created as dependent variables) have not been simultaneously optimized for these types of problems.

The aim of the multi-objective mixed-integer linear programming (MO-MILP) model developed in this research is to obtain logistics decisions for a multi-echelon supply chain with six levels. The first objective in the MO-MILP model focuses on the economic aspect by considering total cost, which is used to estimate the cost of the final product. The second objective focuses on the environmental impact of the supply chain, which is predicted using carbon footprint analysis. The third objective considers the societal effects by considering at the number of jobs created in the supply chain.

5.4 Research Limitations

Several activities in bio-oil supply chains were studied and modeled as part of this research. However, the lack of access to the conversion processes prevented providing a more accurate estimation of the cost of bio-oil. To improve this limitation, sensitivity analysis was performed by varying the percentage yield to discern the effect of conversion processes on the outputs of bio-oil supply chains. In modeling the bio-oil supply chain presented herein, all parameters were assumed to be defined and deterministic. In reality though, parameters are fuzzy and stochastic. For example, it was found that the percentage yield parameter significantly impacts bio-oil supply chain performance. These parameters need to be better understood and more accurately quantified.

However, percentage yield itself is not a stable parameter. Since weather conditions are unpredictable, and impact biomass feedstock quality, the expected yield is not deterministic. Similarly, the available woody biomass depends on weather and market conditions, and could be modeled using a stochastic parameters rather than the deterministic parameter used in this work to enhance the robustness of the model.

The just-in-time approach is an innovative method to avoid inventory costs in supply chains, as applied in this research. In reality, however, maintaining an inventory of raw materials is often necessary to optimize the total cost of transportation. For example, the bio-oil produced may be stored in a large tanker to be transported later, rather than using a small tanker truck, to reduce the number of truck trips and associated labor and fuel costs.

Regarding data collected from northwest Oregon, data for only four counties are considered for a short time period. This dearth of data can lead to a poor prediction of the cost of bio-oil, number of jobs created, and carbon footprint. This leads to decision maker hesitation and inaction, as has been evidenced by the protracted development of forest bioenergy supply chains.

5.5 Opportunities for Future Research

Due to the limitations above, several opportunities for future research have been identified. They include improving the accuracy of the sustainability assessment methodology, incorporating a more efficient multi-objective mathematical models for decision making, and optimizing input parameters to achieve greater sustainability performance. These opportunities are discussed below.

To help managers in bio-oil supply chains make better and more informed decisions, values of supply chain parameters, e.g., percentage yield and refinery capacity, need to be more well-defined quantitatively. Alternatively, modeling the parameters of bio-oil supply chains using stochastic approach would allow for a more quantitative investigation of tradeoffs between objectives such as the total cost, carbon footprint, and number of jobs created.

In reality, maintaining an inventory of biomass or bio-oil is often necessary to optimize the total cost of transportation, while the just-in-time approach is used in supply chains to avoid inventory costs. If the assumption of the just-in-time approach in the inventory management of the bio-oil supply chain is relaxed, inventory costs should be included in the total cost of bio-oil supply chains. Then, the total cost objective should include ordering cost, holding cost, backorder and lost sales in the mathematical model.

To assist managers of bio-oil supply chains in decision making when considering all forests in a state or region, the design decision support tool presented herein needs to be solved with powerful solving methods, e.g., decomposition methods, due to the high complexity of the mathematical model created by large-scale data. The mathematical model presented herein was solved using the branch and cut method with CPLEX software. The solution method presented in this work cannot be used to optimize a large-scale bio-oil problem. A new solution algorithm, such as hybrid meta-heuristic algorithms and decomposition methods, could be developed to solve large-scale bio-oil problems.

To more accurately evaluate the indicator of number of jobs used in the societal objective function, other employment positions, such as loggers, forestry machine operators, and truck drivers, in addition to refinery employees, should be considered in future research.

Finally, while the mathematical models were developed to enable supply chain decision making over multiple harvesting cycles occurring over a longer period of time (years or decades), the model was demonstrated for a single time period (one harvesting season). To accommodate evaluation of larger harvest regions and longer time periods (e.g., facilitating more accurate modeling of mobile refinery transport, utilization, and production), future work should investigate the mathematical model can be employed within an approximate dynamic programming problem.

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APPENDICES

Appendix A: MATLAB source code

```
clc;
clear;
close all;
 global NFE;
%% Problem Definition
load('model_3_5_7_8_2.mat')  % small
% load('model_20_8_6_4_2.mat') %large
 % model=SelectModel();
CostFunction=@(sol) MyCost(sol,model);
 tic;
%% GA Settings
nPop=50;                   % Population Size
 MaxIt=1000;                 % Maximum Number of Iterations
 MaxStallIt=round(MaxIt/1);
 pCrossver=0.5;                        % Crossover Percentage
nCrossover=round(pCrossover*nPop/2)*2;  % Number of Parents (Offsprings)
 pMutation=0.8;                         % Mutation Precentage
nMutation=round(pMutation*nPop);       % Number of Mutatnts
 SelectionPressure=10;       % Selection Pressure
TournamentSelectionSize=3;
 %% Initialization
NFE=0;
% An Empty Individual Structure
Individual.Position=[];
Individual.Cost=[];
Individual.Sol=[];
 % An Array of Individuals
pop=repmat(Individual,nPop,1);
 % Initialization
for i=1:nPop
pop(i).Position=CreateRandomSolution(model);
[pop(i).Cost pop(i).Sol]=CostFunction(pop(i).Position);
 end
 BestSol=[];                 % Best Solution Ever Found
 BestCost=zeros(MaxIt,1);    % Array of Best Costs at each Iteration
MeanCost=zeros(MaxIt,1);    % Array of Mean Cost at each Iteration
 MaxCost=-inf;              % Maximum Cost Ever Found
 nfe=zeros(MaxIt,1);
 StallIt=0;
```

```
 for it=1:MaxIt
 % Sort Population
costs=[pop.Cost];
[costs sort_order]=sort(costs);
pop=pop(sort_order);
 % Update Maximum Cost
MaxCost=max(MaxCost,costs(end));
 % Delete Extra Members
pop=pop(1:nPop);
costs=costs(1:nPop);
 % Save Results
BestSol=pop(1);
BestCost(it)=costs(1);
MeanCost(it)=mean(costs);
 nfe(it)=NFE;
 % Show Results
penalty=Penalty(BestSol.Sol.sol,model);
disp(['Iteration ' num2str(it) ...
':  Best Cost = ' num2str(BestCost(it)-max(0,penalty)) ...
':  Penalty = ' num2str(penalty) ...
', Mean Cost = ' num2str(MeanCost(it))  ]);
 % dynamic figure
figure(1);
clf(figure(1))
sol=BestSol.Sol.sol;
PlotSolution(sol,model);
  % At Last Iteration
if it==MaxIt
break;
end
 % Calculate Selection Probabilities
P=exp(-SelectionPressure * costs / MaxCost);
P=P/sum(P);
 %% selection Crossover
pop2=repmat(Individual,nCrossover/2,2);
for k=1:nCrossover/2
 %        i1=RouletteWheelSelection(P);   %randi([1 nPop]);
%        i2=RouletteWheelSelection(P);   %randi([1 nPop]);
 i1=TournamentSelection(pop,TournamentSelectionSize);
i2=TournamentSelection(pop,TournamentSelectionSize);
 p1=pop(i1);
p2=pop(i2);
 ch1.Position = p1.Position;
ch2.Position = p2.Position;
```

```
[ch1.Position.BXij,ch2.Position.BXij]=CrossoverTwoPoint(p1.Position.BXij,p2.Position.
BXij);
[ch1.Position.BXik,ch2.Position.BXik]=CrossoverTwoPoint(ch1.Position.BXik,ch2.Posit
ion.BXik);
 ch1.Position=repairSOL(ch1.Position,model);
ch2.Position=repairSOL(ch2.Position,model);
 [ch1.Cost ch1.Sol]=CostFunction(ch1.Position);
[ch2.Cost ch2.Sol]=CostFunction(ch2.Position);
 pop2(k,1)=ch1;
pop2(k,2)=ch2;
 end
pop2=pop2(:);  % pop2=reshape(pop2,[],1);
 %% Mutation
pop3=repmat(Individual,nMutation,1);
for k=1:nMutation
 i=randi([1 nPop]);   %randi([1 nPop]);
 %  q.Position=CreateRandomSolution(model);
 q=pop(i);
 q.Position.BXij(2:end,:)=Mutate(pop(i).Position.BXij(2:end,:));
q.Position.BXik(2:end,:)=Mutate(pop(i).Position.BXik(2:end,:));
 q.Position=repairSOL(q.Position,model);
 end
 %%
%% Mutation
pop4=repmat(Individual,nMutation,1);
for k=1:nMutation/2
 i=randi([1 nPop]);   %randi([1 nPop]);
 q.Position=CreateRandomSolution(model);
[q.Cost q.Sol]=CostFunction(q.Position);
 end
 %% Merge Main, Offspring, and Mutant Populations
pop=[pop
pop2
pop3
pop4]; %#ok
 if it>1                                  % add for other stop
if BestCost(it-1)==BestCost(it)
StallIt=StallIt+1;
else
StallIt=0;
end
end
 if StallIt>=MaxStallIt
break;
```

```
end
 end
 BestCost=BestCost(1:it);    % add for other stop
MeanCost=MeanCost(1:it);    % add for other stop
nfe=nfe(1:it);    % add for other stop
 %% Results
sol=BestSol.Sol.sol
figure(2);
PlotSolution(sol,model);
PlotSolutionNotOptimal(sol,model)
 figure(3);
% subplot(2,1,1);
loglog(BestCost,'b ','LineWidth',2);
hold on;
%loglog(MeanCost,'r:','LineWidth',2);
legend('The Best Cost');
xlabel('Iteration of GA');
ylabel('Cost Function');
 xlim([0 it(end)+10]);
ylim([0 BestCost(1)+5000]);
 figure(4);
PlotSolution(sol,model);
 CPU_Time=toc
The_Cost_Function=BestCost(it);
 % the decision variables
BXij=sol.BXij;
BXik=sol.BXik;
BXjk=sol.BXjk;
BXjl=sol.BXjl;
%   BYkl=sol.BYkl;
%   BYls=sol.BYls;
 Xij=BXij(2:end,:);
Xik=BXik(2:end,:);
Xjk = BXjk(2:end,:);
Xjl=BXjl(2:end,:);
```

Appendix B: CPLEX source code

```
/*********************************************
 * OPL 12.5 Model
 * Author: Sadeghi
 * Creation Date: Aug 31, 2017 at 5:21:43 PM
 *********************************************/
// Parameters
int I=...; // number of harvesting sites
int J=...; // number of Mobile Refineries (MR)
int K=...; // number of Junctions of main road
int L=...; // number of Fixed refineries
int A=...; // Employees' area
int W=...; // number of warehouses
int V=...; // number of Vehicles
int NumberHarvestingSitesInClatsop=...;
int NumberHarvestingSitesInColumbia=...;
int NumberHarvestingSitesInTillamook=...;
int NumberHarvestingSitesInWashington=...;
float BiomassInClatsop=...;
float BiomassInColumbia=...;
float BiomassInTillamook=...;
float BiomassInWashington=...;
range harvesting = 1..I;
range Junc = 1..K;
range MRef = 1..J;
range Ref = 1..L;
range Warehouse = 1..W;
range Vehicles = 1..V;
range OpenCloseLocation = 1..4;
range Area = 1..A;
range JobSite = 1..5; // i, j, k, l, w
float VarCostPerTon[1..4]=...;
float CostOfForestResidue=...;
float ProductionCapacity[1..2]=...;
float Dij[harvesting][MRef]=...;
float Dik[harvesting][Junc]=...;
float Dkl[Junc][Ref]=...;
float Dlw[Ref][Warehouse]=...;
float Djw[MRef][Warehouse]=...;
float Daj[Area][MRef]=...;
float Dal[Area][Ref]=...;
float Daw[Area][Warehouse]=...;
```

```
float Cv[Vehicles]=...;
float Vc[Vehicles]=...;
float FacilityLocationCost[OpenCloseLocation]=...; // k, j, l, w
int FacilityLocationWarehouseCost[Warehouse]=...;
int WarehouseStorageCapacity[Warehouse]=...;
float ce[JobSite]=...;
float salary=...;
float S=...;
float StorageCapacity[1..5]=...;
int bb=...;
float HH[1..3]=...;
float EmpCap[Area]=...;
float GHGe=...;
float GHGB=...;
float G_CO2_Truck[Vehicles] = ...;
 // variables
 dvar float+ xij[harvesting][MRef];
 dvar float+ xik[harvesting][Junc];
 dvar float+ xkl[Junc][Ref];
// dvar float+ Yjl[MRef][Ref];
 dvar float+ Yjw[MRef][Warehouse];
 dvar float+ Ylw[Ref][Warehouse];
 // dependent variables
 dvar float+ xi[harvesting];
 dvar float+ x_all;
 dvar float+ xj_all;
 dvar float+ xk_all;
 dvar float+ xk[Junc];
// dvar float+ xj[MRef];
 dvar float+ Yj[MRef];
 dvar float+ Yj_all;
 dvar float+ Yw_all;
 dvar float+ Yw[Warehouse];
 dvar int+ zk[Junc];
 dvar int+ zj[MRef];
 dvar int+ zl[Ref];
 dvar int+ zw[Warehouse];
 dvar float+ Labaj[Area][MRef];
 dvar float+ Labal[Area][Ref];
 // dependent variables
 dvar float+ Lab_a_all[Area];
 dvar float+ Lab_all;
 // number of empoyees working in i
 dvar float+ NEMj[MRef];
```

```
dvar float+ NEMl[Ref];
// dependent variables
dvar float+ NEMj_all;
dvar float+ NEMl_all;
// variables # trips
dvar int+ Nij[harvesting][MRef];
dvar int+ Nik[harvesting][Junc];
dvar int+ Nkl[Junc][Ref];
dvar int+ Njw[MRef][Warehouse];
dvar int+ Nlw[Ref][Warehouse];
//---------- Expressions --
dexpr float Cost_ForestResidue = CostOfForestResidue*x_all ;
dexpr float Cost_Transportation =
sum(i in harvesting, j in MRef) Dij[i][j]*Cv[1]* Nij[i][j] +
sum(i in harvesting, k in Junc) Dik[i][k]*Cv[1]* Nik[i][k] +
sum(k in Junc, l in Ref) Dkl[k][l]*Cv[2]* Nkl[k][l] +
sum(j in MRef, w in Warehouse) Djw[j][w]*Cv[3]* Njw[j][w] +
sum(l in Ref, w in Warehouse) Dlw[l][w]*Cv[4]* Nlw[l][w] ; // TR
dexpr float Cost_TotalFacilityLocation =
sum(k in Junc) zk[k] * FacilityLocationCost[1] + VarCostPerTon[1]*(sum(i in
harvesting,k in Junc) xik[i][k]) +
sum(j in MRef) zj[j] * FacilityLocationCost[2] + VarCostPerTon[2]*(sum(j in MRef,w
in Warehouse) Yjw[j][w]) +
sum(l in Ref) zl[l] * FacilityLocationCost[3] + VarCostPerTon[3]*(sum(l in Ref, w in
Warehouse) Ylw[l][w]) +
sum(w in Warehouse) zw[w] * FacilityLocationWarehouseCost[w] +
VarCostPerTon[4]*(sum(w in Warehouse) Yw[w]) ;
dexpr float CostFunction_Total = Cost_TotalFacilityLocation + Cost_Transportation +
Cost_ForestResidue ;
dexpr float SocialEffects =
(((sum(j in MRef, w in Warehouse) HH[1] * Yjw[j][w] ) / bb +
(sum(l in Ref, w in Warehouse) HH[2] * Ylw[l][w] ) / bb ) +
(9*(sum(j in MRef) zj[j] +sum(l in Ref) zl[l] ))) ;
dexpr float GHG_by_Employees_Transportation =
GHGe * (
sum(a in Area, j in MRef)Daj[a][j] * Labaj[a][j] +
sum(a in Area, l in Ref)Dal[a][l] * Labal[a][l] );
dexpr float GHG_by_ProducingBiooil = GHGB * Yw_all;
dexpr float GHG_by_Product_Transportation =
G_CO2_Truck[1] * (sum(i in harvesting, j in MRef) Dij[i][j]* Nij[i][j] +
sum(i in harvesting, k in Junc) Dik[i][k]* Nik[i][k] )+
 G_CO2_Truck[2] * (sum(k in Junc, l in Ref) Dkl[k][l]* Nkl[k][l] )+
G_CO2_Truck[3] * (sum(j in MRef, w in Warehouse) Djw[j][w]* Njw[j][w] )+
G_CO2_Truck[4] * (sum(l in Ref, w in Warehouse) Dlw[l][w]* Nlw[l][w] );
```

```
 dexpr float Carbon_Dioxide_Equivalent_CO2e =
 GHG_by_Employees_Transportation +
 GHG_by_ProducingBiooil +
 GHG_by_Product_Transportation ;
 dexpr float Price = CostFunction_Total/ (0.26417205235815*1000*Yw_all);
 dexpr float PriceLit = CostFunction_Total/ (1000*Yw_all);
dexpr float The_Number_Of_Truck_Trip = sum(i in harvesting, k in Junc) Nik[i][k] + (i
in harvesting, j in MRef) Nij[i][j] +sum(k in Junc, l in Ref) Nkl[k][l] +sum(j in MRef,w
in Warehouse) Njw[j][w] +sum(l in Ref, w in Warehouse) Nlw[l][w] ;
 dexpr float Active_Mobile_Refineries = sum(j in MRef) zj[j];
 dexpr float Active_Fixed_Refineries = sum(l in Ref) zl[l];
 dexpr float Active_Collection_sites = sum(k in Junc) zk[k];
 dexpr float Active_Warehouses = sum(w in Warehouse) zw[w];
// ------------------------------------------------Model---------------------------------------------
minimize (1/3)*(CostFunction_Total/819769) +
(1/3)*(Carbon_Dioxide_Equivalent_CO2e/3507) - (1/3)*(SocialEffects/347);
// ---------------------------------------Constraints------------------------------------------------
 subject to {
  // ------------------------------Number Of Truck--------------------------------------
 forall(i in harvesting, j in MRef)Constraint001:Nij[i][j] >= (xij[i][j] / Vc[1]) ;
 forall(i in harvesting, k in Junc)Constraint002:Nik[i][k] >= (xik[i][k] / Vc[1]) ;
 forall(k in Junc, l in Ref)Constraint003:Nkl[k][l] >= (xkl[k][l] / Vc[2]) ;
 forall(j in MRef,w in Warehouse)Constraint004:Njw[j][w] >= (Yjw[j][w] / Vc[3]) ;
 forall(l in Ref, w in Warehouse)Constraint005:Nlw[l][w] >= (Ylw[l][w] / Vc[4]) ;
 // ------------------------------Percentage yield-------------------------------------
 forall(j in MRef)Constraint006:sum(i in harvesting) S*xij[i][j] == sum(w in Warehouse)
Yjw[j][w]; //-bio-oil from bio-mass regarding percentage yield i-j
 forall(k in Junc) Constraint009:sum(i in harvesting) xik[i][k] == sum(l in Ref) xkl[k][l];
//-input and output-
 forall(l in Ref)Constraint077:sum(k in Junc) S*xkl[k][l] == sum(w in Warehouse)
Ylw[l][w]; //-bio-oil from bio-mass regarding percentage yield k-l
 forall(w in Warehouse)Constraint007: sum(j in MRef) Yjw[j][w] + sum(l in Ref)
Ylw[l][w] == Yw[w];
 // forall(l in Ref)Constraint008:sum(k in Junc) S*xkl[k][l] == Yl[l]; //-bio-oil from bio-
mass regarding percentage yield k-l
 // -------------------------------Open/Close Sites-------------------------------------
 forall(j in MRef)Constraint010:sum(i in harvesting) xij[i][j] <= zj[j]*10000000000;
 forall(k in Junc)Constraint011: sum(i in harvesting) xik[i][k] <= zk[k]*10000000000; //
Open/Close Sites: Junctions
 forall(w in Warehouse)Constraint012:sum(j in MRef) Yjw[j][w] <=
zw[w]*10000000000;// Open/Close Sites: Ref
 forall(l in Ref)Constraint013:sum(k in Junc) xkl[k][l] <= zl[l]*10000000000;//
Open/Close Sites: Ref
 forall(w in Warehouse)Constraint014: sum(l in Ref) Ylw[l][w] <=
```

```
zw[w]*10000000000;// Open/Close Sites: Ref
 // -------------------------------Open/Close Sites & Number of Employees----------------------
----------------
 forall(j in MRef)Constraint0141: sum(a in Area) Labaj[a][j] <= zj[j]*10000000000;
 forall(l in Ref)Constraint0142: sum(a in Area) Labal[a][l] <= zl[l]*10000000000;
// -------------------------------Capacity Storage-------------------------------------
 forall(k in Junc)Constraint016:sum(i in harvesting) xik[i][k] <= StorageCapacity[1];// k
 forall(j in MRef)Constraint015:sum(i in harvesting) xij[i][j] <= StorageCapacity[2]; // j
 forall(l in Ref)Constraint017:sum(k in Junc) xkl[k][l] <= StorageCapacity[3];// l for bio-
mass
 forall(j in MRef)Constraint818:sum(w in Warehouse) Yjw[j][w] <=
StorageCapacity[4];// l for bio-oil
 forall(l in Ref)Constraint018:sum(w in Warehouse) Ylw[l][w] <= StorageCapacity[5];// l
for bio-oil
 forall(w in Warehouse)Constraint0182:sum(j in MRef) Yjw[j][w] <=
WarehouseStorageCapacity[w];
 forall(w in Warehouse)Constraint019:sum(l in Ref) Ylw[l][w] <=
WarehouseStorageCapacity[w];// w
  // -------------------------------Production Capacity-------------------------------------
 forall(j in MRef)Constraint091:sum(w in Warehouse) Yjw[j][w] <=
1*ProductionCapacity[1];
 forall(l in Ref)Constraint0181:sum(w in Warehouse) Ylw[l][w]<=
1*ProductionCapacity[2];
// we used integer instead of bulian as it was faster
 forall(j in MRef)Constraint0101:zj[j] <=1;
 forall(k in Junc)Constraint0111: zk[k] <=1;
 forall(w in Warehouse)Constraint0121:zw[w] <=1;
 forall(l in Ref)Constraint0131:zl[l] <=1;
 forall(i in harvesting) Constraint02701: xi[i] == .0005* 9.225*1000000/(43); // (11.5 +
6.1 + 13.2 + 6.1)/4 = 9.225
 forall(i in harvesting)sum(k in Junc) xik[i][k] + sum(j in MRef) xij[i][j] >= xi[i];
 forall(j in MRef)Constraint021: sum(a in Area) Labaj[a][j] == 9*zj[j] +(sum(w in
Warehouse) HH[1] * Yjw[j][w]) / bb;
 forall(l in Ref)Constraint022: sum(a in Area) Labal[a][l] == 9*zl[l] + (sum(w in
Warehouse) HH[2] * Ylw[l][w]) / bb;
 forall(a in Area) Constraint024: sum(j in MRef) Labaj[a][j] <= EmpCap[a];
 forall(a in Area) Constraint025: sum(l in Ref) Labal[a][l] <= EmpCap[a];
 // ------------------------------Dependent Constraints---
 forall(j in MRef) DependentConstraint001: NEMj[j] == sum(a in Area) Labaj[a][j];// CE
changed to b
 forall(l in Ref) DependentConstraint002: NEMl[l] == sum(a in Area) Labal[a][l];
 DependentConstraint006: xj_all == sum(i in harvesting, j in MRef) xij[i][j];
 DependentConstraint007: xk_all == sum(i in harvesting, k in Junc) xik[i][k];
 forall(k in Junc)DependentConstraint008: xk[k] == sum(i in harvesting) xik[i][k];
```

```
 DependentConstraint009: x_all == xj_all + xk_all;
 forall(j in MRef)DependentConstraint010: Yj[j] == sum(w in Warehouse) Yjw[j][w];
 DependentConstraint013: Yj_all == sum(j in MRef, w in Warehouse) Yjw[j][w];
 DependentConstraint015: Yw_all == sum(w in Warehouse)Yw[w];
DependentConstraint017: Lab_all == sum(a in Area) Lab_a_all[a];
DependentConstraint018: NEMj_all == sum(j in MRef) NEMj[j];
DependentConstraint019: NEMl_all == sum(l in Ref)NEMl[l];
 } /####################################################
 execute {
 writeln("Objectives: " )
 writeln("Total Cost $:" , Math.round(CostFunction_Total))
 writeln("Total Carbon footprint Kg:" , Math.round(Carbon_Dioxide_Equivalent_CO2e))
 writeln("The Number of Employees #:" , SocialEffects)
 writeln()
 writeln("Actual Cost of Bio-oil $ per Lit.: ", PriceLit);
 writeln("Actual Cost of Bio-oil $ per Gallon: ", Price)
  writeln()
 writeln("Costs: " )
 writeln("Facility Location Cost: " , Math.round(Cost_TotalFacilityLocation))
 writeln("Transportation Cost: " , Math.round(Cost_Transportation))
 writeln("ForestResidue Cost: " , Math.round(Cost_ForestResidue))
  writeln()
 writeln("The CO2 eq. of Empl. Trans.(kg):",
Math.round(GHG_by_Employees_Transportation))
 writeln("The CO2 eq. of Bio-oil: ", Math.round(GHG_by_ProducingBiooil))
 writeln("The CO2 eq. of Transportation: ",
Math.round(GHG_by_Product_Transportation))
  writeln()
 writeln("The Number Of Truck Trip: ", The_Number_Of_Truck_Trip)
  writeln()
 writeln("Details: " )
 writeln("The Total Biomass (ton): ", Math.round(x_all))
 writeln("The Total Bio-oil (Lit.): ", Math.round(Yw_all*1000))
  writeln()
 writeln("Active Locations: " )
 writeln("Active_Mobile_Refineries: " , Active_Mobile_Refineries)
 writeln("Active_Fixed_Refineries: " , Active_Fixed_Refineries)
 writeln("Active_Collection_sites: " , Active_Collection_sites)
 writeln("Active_Warehouses: " , Active_Warehouses )
 }
```