ABSTRACT

A MULTI-OBJECTIVE ROBUST ALGAL BIOFUEL SUPPLY CHAIN UNDER UNCERTAINTY

Keivan Ghasemi Nodooshan, MS
Department of Industrial and Systems Engineering
Northern Illinois University, 2017
Dr. Reinaldo Moraga, Co-Advisor
Dr. Shi-Jie (Gary) Chen, Co-Advisor

Energy has historically been of great importance to the world. Depletion of fossil fuels, growing demand, global warming, and etc. have even accentuated this importance more. Amongst the biomass for production of biofuel which is one of the most promising renewable energy options, algae have been gaining a lot of attention in recent years. This thesis will propose a Biofuel Supply Chain Network Design for the development of algal biofuels. In order to do so, a Mixed Integer Linear Program will be created to design and optimize a biofuel supply chain from raw material procurement to biofuel distribution. Furthermore, a robust optimization method will be utilized to enable the model to cope with uncertainties of the biofuel supply chain. In addition, an environmental objective would be considered alongside an economic objective both of which are optimized by augmented ε-Constraint method to address issues such as global warming.

Keywords: Algal biofuel, Robust optimization, Multi objective optimization, ε-Constraint

NORTHERN ILLINOIS UNIVERSITY

DE KALB, ILLINOIS

AUGUST 2017

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BY

KEIVAN GHASEMI NODOOSHAN
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A THESIS SUBMITTED TO THE GRADUATE SCHOOL

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE

MASTER OF SCIENCE

DEPARTMENT OF INDUSTRIAL AND SYSTEMS ENGINEERING

Thesis Co-Directors:

Reinaldo Moraga

Shi-Jie (Gary) Chen

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1. Introduction

A supply chain comprises all the processes and efforts involved in production and distribution of a good from the procurement level to delivery. The introduction of supply chain management helped the obsolescence of the narrow perspective of looking only into one part of a business at a time, thus enabling decision makers and researchers to look at one integrated entity while making decisions regarding each individual section and tackling its associated problems. The approach prior to supply chain management was based on the notion that an intricate problem would be simplified by disintegrating it which neglects the fact that not being able to see a system as a whole often results in suboptimal decisions due to overlooking the interactions of that system. In other words, as Senge (1990) puts it, “Dividing an elephant in half does not produce two small elephants.” Supply chains can be defined and are used for a wide variety of goods ranging from toys and food merchandise to high tech parts of aerospace industry.

Supply chain of biofuels as one of the most promising alternatives of fossil fuels needs to be studied if biofuels are to replace the fossil fuels and contribute to satisfaction of world’s energy demand. Renewable energy sources contribute to meeting 14% of global primary energy demand and biomass from which biofuel is produced boasts 11.5% of global energy demand which is 82% of all renewable energies. Biomass is still attracting interest of researchers and investors and its contribution is estimated to increase to 15-50% of global primary energy by the year 2050 (Bahrami & Abbaszadeh, 2013). The first generation of biofuels is produced from food crops which are mostly corn, wheat, and sugar cane (Biofuel.org.uk, 2010a); the second generation from energy crops, food crops residues, and food crops themselves after fulfillment of their food purposes (Biofuel.org.uk, 2010b); the third generation from algae (Biofuel.org.uk, 2010c). Algal biofuel has been attracting interest as the next generation of biofuels due to several characteristics of microalgae including:

1) High productivity: microalgae doubling time (i.e. time required for doubling the biomass) is commonly 24 hours with the potential of being reduced to 3.5 hours during exponential growth. In addition, oil content (i.e. percent of oil in dry weight biomass) of 20-50% is quite common for microalgae and can even exceed 80% in certain species (Chisti, 2007). Table 1 compares the oil yield and land requirement of microalgae with some of commercial sources of biodiesel in United States.

Table 1: Oil yield and land requirements of biodiesel sources (Chisti, 2007)

Crop	Oil Yield (Gallon/ha)	Percent of existing US cropping area *
Corn	45	846
Soybean	118	326
Canola	314	122
Jatropha	500	77
Oil Palm	1,572	24
Microalgae	15,507	2.5

* Required for meeting 50% of all transport fuel needs of the United States

2) Minimized competition with agriculture and food industries: as microalgae can be cultivated in non-arable lands and utilize saline, brackish, and wastewater in addition to fresh water. (Ferrell & Sarisky-Reed, 2010).

3) Production of multiple biofuels: biodiesel, methane, bio hydrogen, and also valuable co-products are amongst the microalgae products (Chisti, 2007; Ferrell & Sarisky-Reed, 2010).

4) Recycling CO_2: CO_2 required for algae cultivation can be provided from stationary sources such as power plants and other industries and hence mitigating Green House Gas (GHG) emissions (Mata et al., 2010).

5) Compatibility with existing infrastructure: Existing refineries, tanks, pipelines, vehicles, etc. need not be changed to use the algal biofuels which can save astronomically high capital investment costs. (Yue, 2013)

A prominent trait of a supply chain or more accurately supply network regardless of the industry in which the research is conducted is its echelons. The echelons of biofuel supply networks vary depending on the generation of biofuel, production method, final products, and many other factors. Algal biofuel supply networks are comprised of the three major echelons named procurement, production, and distributions. The procurement level deals with obtaining the raw materials for feedstock cultivation, providing or growing the feedstock, and etc. This level can be further divided into multiple ones depending on the problem specifications. The production and transportation levels can also be broken down into different levels due to the need of distributions hubs, centralized or distributed production plants, and so forth. The echelons of this article would be discussed in the following sections.

The algal biofuel industry is in its genesis stage and researches in this area are dedicated to establishing the role of algal biofuels in the future of energy industry. In order to do so, numerous factors should be considered in a variety of analyses. Such factors are associated with uncertainties even in industries which have been in existence for decades as a lot of determinants like competition, new developments, economy, and etc. affect these factors. The nascency of the biofuel industry especially algal biofuel highlights the need for incorporation of these uncertainties in the field's researches. In addition, the nature of algal biofuel also necessitates the consideration of uncertainties. As an instance, inherent attributes like being in correlation with elements such as weather which are known for their capriciousness. Taking such real world problems into account contributes to increase of the research's credibility and applicability. Growing competition over dwindling fossil fuel reservoirs caused by increasing energy demand in rapidly developing countries might be the most important incentive of governments to stimulate renewable energies researches but grievous issues such as global warming should not be disregarded. Cost competitiveness has always been the most paramount factor of decision making historically and the importance of all other issues has paled in comparison to that of cost competitiveness. However, since biofuels as a solution to the energy problem of today should not become tomorrow's trouble, factors such as GHG emission and total energy yield should be addressed in addition to the supply chain value or in other words price of biofuels.

1.1 Problem Description

Current study designs and optimizes a microalgae derived biofuel supply network with the goal of contributing to the development of a national, commercial scale, and sustainable biofuel industry. The supply network studied in this research is a supply network of micro-algal biofuel consisting of three echelons producing biodiesel and other co-products from microalgae. In addition to optimizing the designed supply network, this article would demonstrate the most beneficial areas of focus that future endeavors should be directed towards. Three echelons of this research supply network include procurement, production, and distribution with the procurement level entailing providing the raw material required for microalgae growth, harvesting and drying the microalgae along with incorporation of different available options like purchase of fertilizers or providing the nutrition through use of waste water; production level entailing lipid extraction and conversion alongside other processes involved in producing the biofuel from the feedstock; distribution level being restricted to truck transportation since ground transportation and specifically trucks have proved to be efficient in transporting fuels. The optimization of supply network in this study includes both strategic and operational decisions. As an instance of strategic decisions, locating the areas in which different plants are founded and their production technology can be mentioned which would be achieved by considering multiple potentially suitable locations and associating binary variables with each one; and for operational decisions the amount of biomass transported from cultivation sites to extraction plants. Furthermore, this article tries to overcome the criticism deterministic supply networks face for not being quite applicable in real world by investigating several robust optimization models. The price of fertilizers, supply of raw materials, growth rate, etc. in the procurement echelon; the lipid content, conversion rate, and in production echelon; and final product price and transportation costs in distribution echelon are some instances of the parameters subject to uncertainty in this paper. Finally, the model of designed supply chain would take environmental issues into consideration by investigating a multi objective model which minimizes the GHG emission or maximizes the Net Energy Rate (NER) which is the energy of produced biofuel subtracted by the energy consumed for the production while simultaneously minimizing the costs.

1.2 Benefits and justification

As mentioned earlier, energy is becoming a growing concern around the world. Pressing issues such as rapid depletion of fossil fuel reservoirs, energy security, economic stability, global climate balance, and etc. have prompted governments to invest in renewable energy industry. For instance, United States Department Of Energy (DOE) has recently revived its investment in production of economically viable and environmentally sound algal biofuels. Furthermore, the Energy Independence and Security Act of 2007 (EISA) established a Renewable Fuel Standard (RFS) which mandates the transportation fuel sold in U.S. to include a blending of 36 billion gallons of renewable fuels by 2022 (Ferrell & Sarisky-Reed, 2010)

In addition to the aforementioned potentials and benefits of algal biofuels, even though cellulosic ethanol would play a major role in accomplishing the EISA goal, algae derived biofuels as the next generation of biofuels are able to meet the longer-term requirements of the RFS as algal biomass might offer key characteristics complementary to that of traditional feedstock towards advanced fungible high energy density biofuels. However, in spite of all algal biofuel potential, a significant amount of research, development, and deployment is necessary for sustainable, cost-competitive, and scalable production of algal-based biofuels as the technology state of this field is described to be in its infancy by the experts.

The current study would design a supply network with the goal of commercial scale production of microalgae biofuels based on the available researches of the literature which have focused on algal biology (i.e. strain of algae, growth rate, lipid content, etc.), algal cultivation and downstream processing (i.e. cultivation pathways, harvesting, etc.), algal extraction and biofuel conversion (i.e. lipid extraction, direct production, processing of remnants, etc.), and other technical and economic issues related to algal biofuel. This is due to fact that the authors believed that there is a need for assessing the viability of a real world commercial scale system of algal biofuel production which would help the literature in terms of observing how viable such a system proves to be today and where should the focus of studies be to make it feasible or more efficient. Incorporation of uncertainty and multiple objectives in addition to considering, production technologies, plant locations and multiple time periods to account for seasonal changes in weather condition throughout the year are some examples of striving to make the model as applicable to real world as possible.

1.3 Objective

The objective of this thesis is to develop a multi-objective decision making tool to support strategic and operational decisions associated with a commercial scale micro-algal biofuel supply network.

1.4 Limitations and assumptions

- All the considered locations for plants and resources in this article are limited to Midwest and South area of United States.
- Overall cost has been assumed as minimization objective instead of unit cost to avoid non-linearity in the model.
- Certain technologies of cultivation, harvesting, drying, extraction, conversion, and residue recovery have been grouped and considered together as pathways to avoid computational complexity of considering all grouping scenarios.
- Four time periods have been assumed during a year to reflect seasons and weather conditions.

2. Literature Review

The purpose of thesis as discussed before is to design a robust microalgae-to-biodiesel supply chain network with multiple objectives. A growing interest has been cultivated in studying optimal network design of Biomass Supply Chain (BSC) over the recent decades as the economic, environmental, and efficiency indexes of BSC heavily depend on optimality of its network design. Biomass literature can be divided into researches that focus on technical issues (i.e. algae biology, cultivation technologies, conversion technologies, etc.) and the ones that study the Biomass Supply Chain Network Design (BSCND) focusing on optimization and commercialization of BSC. In this section, the related literature of described problem would be reviewed. This literature review is based on the article by Ghaderi, Pishvaee, and moini (2016). 146 papers dating from 1997 to 2016 gathered by Ghaderi et al. (2016) have been reviewed out of which certain selected articles would be discussed in details. Due to broadness of the described problem branches, the literature has been classified based on traits of BSCND models that are model characteristics (i.e. objective and period), modeling approach (i.e. LP, MILP, etc.), Uncertainty (i.e. deterministic, stochastic, possibilistic), Decisions (i.e. facilities, final product, and biomass), and solution methodologies (i.e. commercial solvers, exact algorithms, and heuristic/meta-heuristic).

The rest of this section is organized as follows: First a few charts that describe the literature aspects are presented to give a general perspective. Second, selected articles and their classification categories are introduced, and finally these categories and articles are discussed in more detail along with some statistic charts.

Figure 1 shows the number of published articles each year which clearly manifests the growing interest in this field. Figure 2 demonstrates the popularity of different solution methodologies and modeling approaches. Figure 3 displays the number of articles that have used a case study or numerical examples as data source for the models.

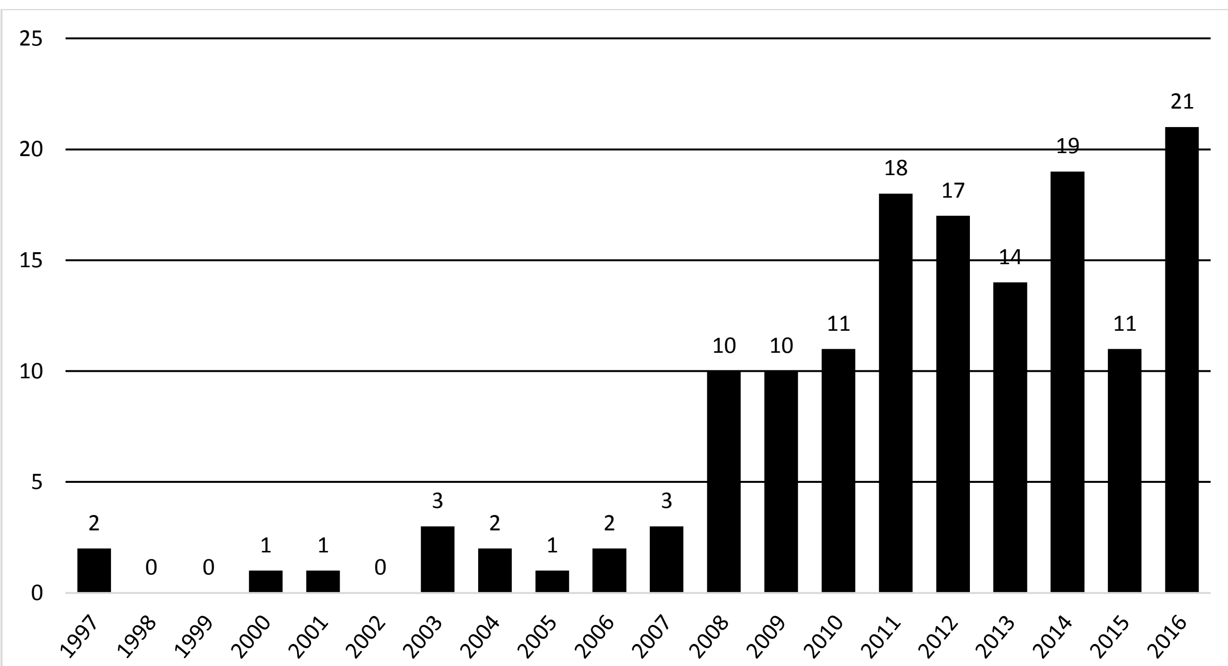


Figure 1: Number of published article each year (Ghaderi et al., 2016)

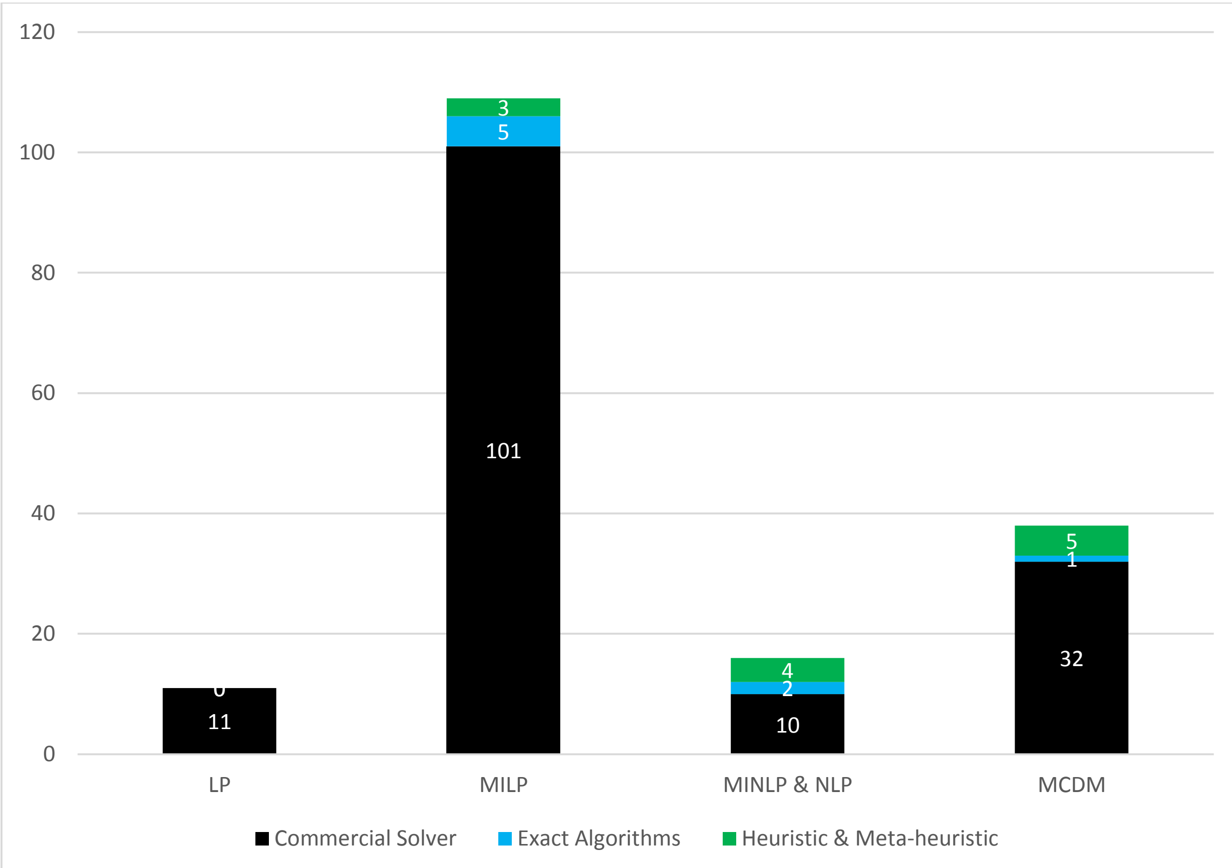


Figure 2: Distribution of utilized modeling approaches and solution methodologies (Ghaderi et al., 2016)

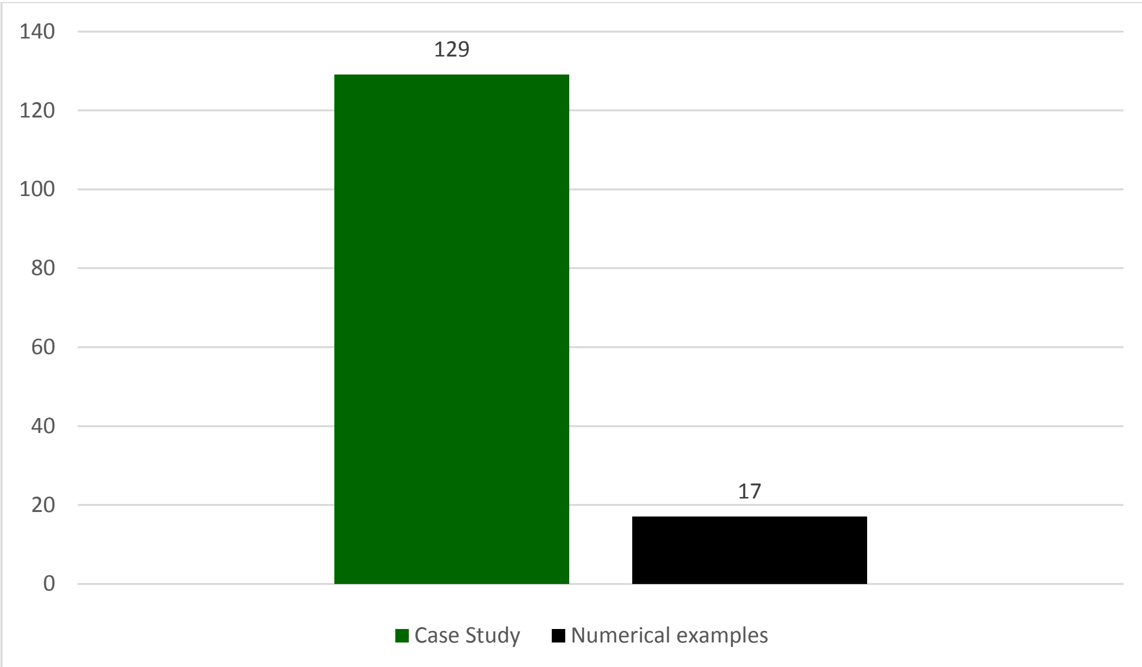


Figure 3: Utilization case study and numerical examples (Ghaderi et al., 2016)

A number of 146 reviewed articles have been chosen for providing further detail. These articles were selected in a way that they reflect most of literature and cover almost all articles that share similarities with this paper. For instance, all the articles that have used algae as feedstock are chosen; almost all of the articles that utilized robust optimization; and also most of the ones that have multiple objectives. Amongst the BSCND traits mentioned earlier the following have been used to categorize the selected articles that will be further investigated:

1. Biomass Feedstock

2. Final Product
3. Modeling Method
4. Multi Period
5. Multi Objective
6. Incorporation of Uncertainty

In addition, the decisions incorporated in the models and the methodology used for solving the model would be mentioned when each article is elaborated on.

Table 2 shows a summary of researches on BSCND under the aforementioned categories.

2.1 Biomass Feedstock and Final Product

A major criterion by which biofuel supply chains are distinguished is the generation and type of feedstock they use. Different biomass feedstock result in different chain configurations, capacities, infrastructures, and so forth. Hence, this decision is one of the most important decisions made in a BSCND and affects almost all other decisions consequently. As mentioned in the first section, there are three generations of biomass. The first generation are edible crops such as corn, soybeans, and sugar cane. These crops which are rich in sugar or oil are used to produce alcohol and diesel with fermentation and transesterification conversion methods respectively. The second generation are crop, forestry, and secondary mill residues, herbaceous crops, animal waste, and energy crops such as Jatropha, Sorghum, and Swithgrass which are converted into fuel in one the four types of biorefineries (i.e. starch-based, sugar-based, oil-based, and lignocellulosic biomass-based) (Sharma et al., 2013). The third generation are algal

Table 2: Literature Review Table

Categories / Sources	Biomass Feedstock	Final Product	Modeling Method	Multi Period	Multi Objective	Uncertainty
An, Wilhelm and Searcy (2011)	Second Generation (Switchgrass)	Ethanol	MILP	X		
Awudu and Zhang (2013)	First generation (Corn)	Ethanol Corn Oil DDGS	LP			X
Azadeh, Arani and Dashti (2014)	Multiple Feedstocks	Gasoline Diesel	MILP	X		X
Kim, Realff, Lee, Whittaker and Furtner (2011b)	Second Generation (Forestry Resources)	Gasoline Diesel	MILP			X
Kim, Realff and Lee (2011a)	Second Generation (Forestry Resources)	Gasoline Diesel	MILP			X
Liu, Qiu, and Chen (2014)	Second Generation (Sweet Sorghum Jatropha & etc.)	Ethanol Methanol Diesel	MILP		X	
Osmani and Zhang (2013)	Second Generation (Switchgrass Corn &Wheat Residue)	Ethanol	MILP			X
Tong, You and Rong (2014)	Second Generation	Gasoline Diesel, Jet Fuel	RMILFP		X	X
Balaman and Selim (2014)	Second Generation (Waste Biomass & Energy Crops)	Biogas	MILP			
You and Wang (2011)	First and Second Generation	Gasoline Diesel	MILP	X	X	
Zhang, Osmani, Awudu and Gonela (2013)	Second Generation (Switchgrass)	Ethanol	MILP	X		

Categories / Sources	Biomass Feedstock	Final Product	Modeling Method	Multi Period	Multi Objective	Uncertainty
Ren, Dong, Sun, Goodsite, Tan and Dong (2015)	First generation (Corn)	Ethanol	LP			X
Sharma, Ingalls, Jones, Huhnke, and Khanchi (2013)	Second Generation (Switchgrass)	Ethanol	LP	X		X
You, Tao, Graziano, and Snyder (2012)	Second Generation	Ethanol	MILP	X	X	
Leduc, Starfelt, Dotzauer, Kindermann, McCallum, Obersteiner, and Lundgren (2010)	Second Generation (Forestry Resources)	Ethanol Biogas Heat Electricity	MILP			
Foo, Tan, Lam, Aziz, and Klemeš (2013)	Second Generation (Palm Residue)	Heat Power	RMILP			X
Marvin, Schmidt, Benjaafar, Tiffany, and Daoutidis (2012)	Second Generation	Ethanol	MILP			
Marufuzzaman, Eksioglu, Li, and Wang (2014)	Biomass	Biofuel	MILP			
Roni, Eksioglu, Searcy, and Jha(2014)	First generation (Corn)	Ethanol	MILP			
Chen and Fan (2012)	Second Generation (Bio-waste)	Ethanol	MILP			X
Gonela, Zhang, and Osmani (2015)	First and Second Generation	Ethanol	MILP	X		X
Azadeh and Arani (2016)	First generation (Soybean)	Diesel	MILP	X		X
Bairamzadeh, Pishvaee, and Saidi-Mehrabad (2015)	First generation (Corn & Wheat)	Ethanol	RMILP	X	X	X

Categories **Sources**	**Biomass Feedstock**	**Final Product**	**Modeling Method**	**Multi Period**	**Multi Objective**	**Uncertainty**
Babazadeh, Razmi, Rabbani and Pishvaee (2015)	Second Generation (Jatropha & waste cooking oil)	Diesel Glycerin	MILP	X		
Santibañez-Aguilar, Morales-Rodriguez, González-Campos, and Ponce-Ortega (2016)	First and Second Generation	Diesel Ethanol	MILP	X	X	X
Cambero and Sowlati (2016)	Second Generation	Bio-oil /Electricity Heat /pellets	MILP	X	X	
Gong and You (2014)	Third Generation	Biofuel Electricity	MINLP		X	
Mohseni, Pishvaee, and Sahebi (2016)	Third Generation	Diesel	RMILP	X		X
Ahn, Lee, Lee, and Han (2015)	Third Generation	Diesel	MILP	X		
Nodooshan (2016)*	Third Generation	Diesel	RMILP		X	X

* Current article LP: Linear Programming MILP: Mixed Integer Linear Programming
RMILP: Robust Mixed Integer Linear Programming MINLP: Mixed Integer Non Linear Programming
RMILFP: Robust Mixed Integer Linear Fractional Programming

which are turned into fuel in oil-based biorefineries (Ferrell & Sarisky-Reed, 2010). Figure 4 shows the number of articles that have used different type of biomass as feedstock in the literature. The total number would not add up to 146 as some articles have considered multiple feedstock and some have not determined the feedstock and hence could not be included in the chart. Further categorization of the biomass has been adapted from Ghaderi et al. (2016). As illustrated by Figure 4, First generation of biofuels comprise 20% of the literature. This number is due to the fact that technologies related to this generation are well established and are already working in commercial scale but as this generation would not be a viable option for meeting a meaningful portion of the world energy demand _due to inefficiency in terms of land and water utilization and also creating a heavy competition for food industry_, their share of research and industry is likely to decrease. The researches related to second generation of biofuels constituting 78.5% of the literature are conducted because this generation eliminates the competition with food industry and is more efficient than the first generation. The Third generation contains only three articles which is due to its nacency and is expected to gain a bigger share of the researches like the second generation but with the third generation's share growing more rapidly.

The final product of a biofuel supply chain similarly affects it as the targeted demand to be satisfied is of great importance. Final product can be one of the factors deemed in mind when choosing feedstock as certain products cannot be produced from all feedstock.

Table 2 gives a summary of feedstock and final product of the selected articles. Below, some of the articles have been chosen to demonstrate examples of how decisions regarding feedstock and final product are made.

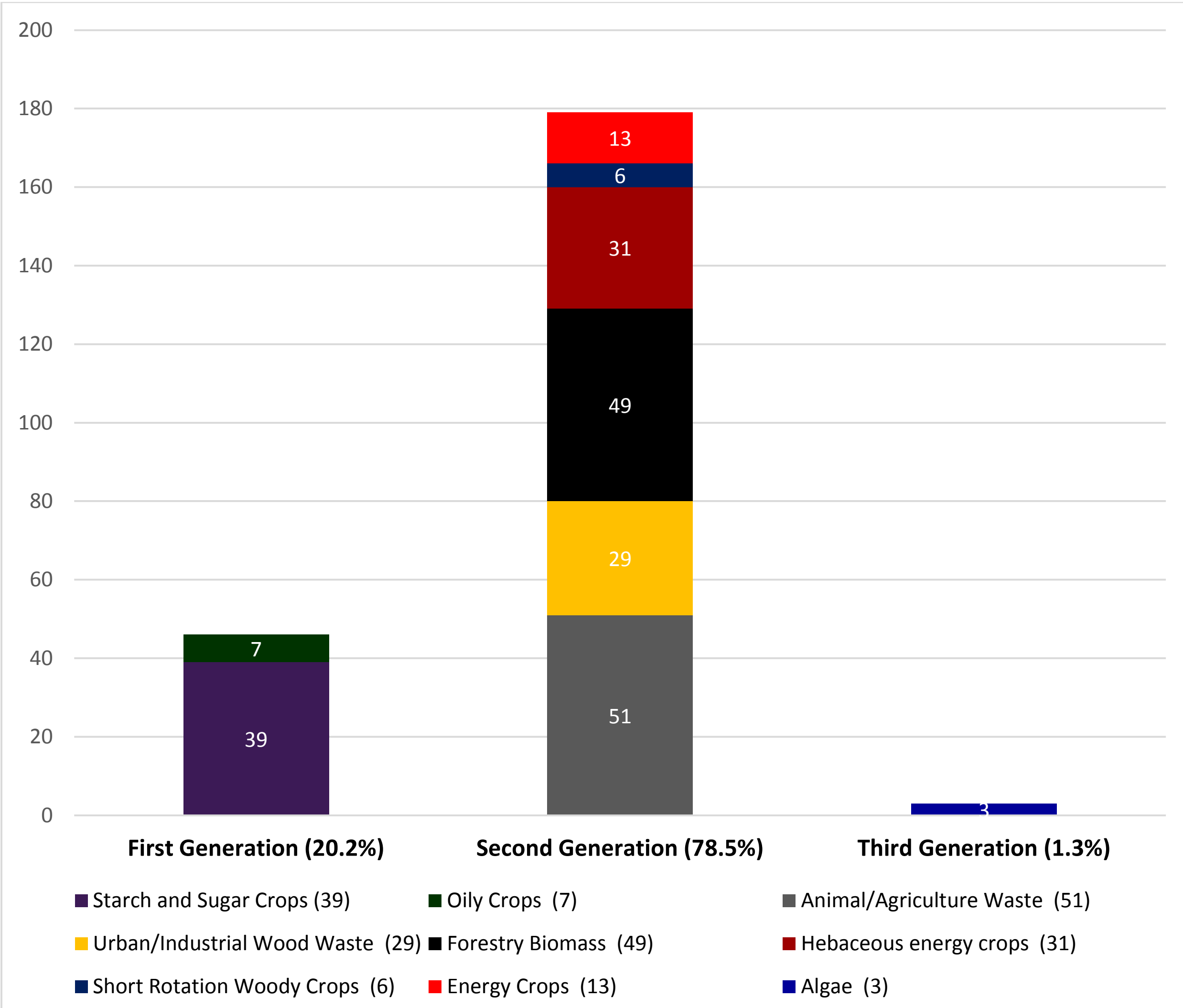


Figure 4: Generation of Biomass distribution

An et al. (2011) developed a switchgrass-to-ethanol supply chain mainly due to switchgrass being able to grow on marginal lands and not competing with agriculture industry for land and ethanol being already used by the current transportation vehicles and not necessitating any modifications. Arani and Dashti (2014) proposed a multiple feedstock to ethanol and bio-diesel supply chain as diversifying the feedstock makes the supply chain more immune to variation of biomass yield. Liu et al. (2014) proposed a supply chain with residues and energy crops as their feedstock and ethanol, methanol, and bio-diesel as the final products. In this article each of the three feedstock yield a different product making what the supply chain offers to the market varied. Osmani and Zhang (2013) added corn and wheat residue to the feedstock of their previous work to enable the supply chain to cope with variations of switchgrass yield.

2.2 Modeling Method

How to model a supply chain is an important question in BSCND literature. Depending on the decision variables, objectives, supply chain components, etc. an approach is chosen for modeling the supply chain. As figure 2 illustrates, MILP is the prevalent modeling method of the literature. This is due to the features that this modeling approach offers such as binary variables which are used for representing the decision of locating facilities and also not having the complexities of nonlinear models. Now the modeling approach of articles mentioned in Table 2 would be discussed and also details of their solution method and decisions.

Majority of these articles have utilized MILP. (An et al., 2011; Azadeh et al., 2014; Kim et al., 2014b; Kim et al., 2014a; Liu et al., 2014; Osmani & Zhang, 2013; Tong et al., 2014; Balaman and Selim, 2014; You & Wang, 2011; Zhang et al., 2013; You et al., 2012; Ludec et al., 2010; Foo et al., 2013; Marvin et al., 2012; Marufuzzaman et al, 2014; Roni et al, 2014; Chen & Fan, 2012; Gonela et al., 2015; Azadeh & Arani, 2016; Bairamzadeh et al., 2015; Babazadeh et al., 2015; Santibañez-Aguilar et al., 2016; Cambero & Sowlati, 2016; Mohseni et al., 2016; Ahn et al., 2015).

An et al. (2011) utilized MILP to locate the facilities and determine their capacity using the binary variables and the model has been solved using a commercial solver. Azadeh et al. (2014) have considered location and capacity of processing facilities along with production technology and have also used commercial software to solve the MILP. Kim et al. (2014a, b), Liu et al. (2014), Osmani & Zhang (2013) have all considered location and capacity of processing facilities except Osmani & Zhang (2013) which have used capacity of supply site instead of processing facility. Ludec et al. (2010) have modeled a poly-generation process for producing multiple products in an integrated facility making the chain more efficient by getting heat and electricity from all possible streams and residues. The decision variables are related to processing sites and biomass allocation. Foo et al. (2013) have formulated the first variant as an LP problem which determines the optimal allocation of biomass between sources and sinks, and also determines the capacities of the combined heat and power plants that utilize the biomass. An improved variant formulated as an MILP model is used to ensure that the biomass allocation for any given source and sink pair in the optimal network meets a minimum threshold quantity. Marvin et al. (2012) have presented an optimization study of the net present value of a biomass-to-ethanol supply chain in a 9-state region in the Midwestern United States. A biochemical technology is assumed for converting five types of agricultural residues into ethanol utilizing dilute acid pretreatment and enzymatic hydrolysis. Optimal locations and capacities of biorefineries are determined simultaneously with biomass harvest and distribution using a MILP model. They have concluded that once the technology has been proven and plants economics evolve, and economic parameters stabilize, there is enough incentive for a 4.7 BGY cellulosic ethanol industry to develop in the region. Marufuzzaman et al. (2014) developed a MILP to determine the optimal intermodal hub locations, and shipment routes of biomass delivery but also hedge against losses of natural disasters disrupting intermodal hubs. Benders decomposition algorithm as an exact algorithm has been used for solving the problem incorporating several algorithmic improvements such as the generation of Pareto-optimality cuts, knapsack inequalities and the trust region cuts. They concluded that the enhanced Benders decomposition algorithm can be used to solve realistic instances of large size problems while constrained Benders decomposition algorithm is capable of producing near optimal solution in a reasonable amount of time. Roni et al (2014) have also used the exact algorithm of Benders decomposition to solve a MILP designed for biomass co-firing in coal-fired power plants. This framework was inspired by existing practices with products with similar physical characteristics to biomass. Chen & Fan (2012) established a MILP to support strategic planning of bioenergy supply chain systems and optimal feedstock resource allocation and utilized a Lagrange relaxation based decomposition solution algorithm to solve it which falls under the heuristic/meta-heuristic solution methods. Gonela et al. (2015) proposed a MILP model aiming to determine the strategic decisions including: operation of existing first generation bioethanol plants with same or expanded capacity or their closure, location, capacity, and collection centers of new second generation bioethanol plants. The method proposed by Azadeh and Arani (2016) first, simulates important parameters of the mathematical programming via a system dynamics model in a given planning horizon. Then, uses a MILP model with those parameters as its data to optimize the supply chain decisions. The MILP utilized by Bairamzadeh et al. (2015) is capable of determining strategic decisions such as biomass sourcing and allocation, locations, capacity levels, and technology types of biorefinery facilities in addition to tactical decisions, including inventory levels, production amounts, and shipments among the network. Babazadeh et al. (2015) developed an integrated hybrid approach utilizing a data envelopment analysis (DEA) and a MILP for the strategic design of biodiesel supply chain network in Iran. A unified DEA first assesses jatropha cultivation areas according to climatic and social criteria. Then the locations with desired efficiency scores are fed to MILP optimizing the numbers, locations and capacities of cultivation, collection, and distribution centers, and bio-refineries. Mohseni et al. (2016) proposed a two-stage model for the BSCND. Their macro-stage performs a spatial filtering using GIS and AHP to identify the most suitable candidate locations for facility foundations which are later applied in the micro-stage. The micro-stage uses a MILP that provides a trade-off between system cost and reliability to determine the strategic and tactical supply chain decisions. Tong et al. (2014) proposed a MILFP and utilized parametric algorithm (Zhong & You, 2014) and reformulation-linearization approach (Yue et al., 2013) which are two efficient tailored solution algorithms for MILFP problems as they take advantage of the efficient mixed-integer linear programming (MILP) methods to globally optimize the MILFP problems. This was due to defining the objective function as unit cost instead total cost. Balaman and Selim (2014), You and Wang (2011), Zhang et al. (2013), You et al. (2012), Cambero and Sowlati (2016), Santibañez-Aguilar et al. (2016), and Ahn et al. (2015) also used different MILPs tailored for their specific problem.

LP has been used by three of the selected articles (Awudu & Zhang, 2013; Ren et al., 2015; Sharma et al., 2013). Awudu and Zhang (2013) utilized linear programming along with Benders decomposition technique and Monte Carlo Simulation to model and solve their problem. The method used by Ren et al. (2015) would be further discussed under the uncertainty subsection as it is an Interval LP specifically used to incorporate uncertainty. Same holds true for Sharma et al. (2013).

Finally, Gong and You (2014), have developed a MINLP model. They utilized a global optimization strategy integrating a branch-and-refine algorithm based on successive piecewise linear approximations along with an exact parametric algorithm based on Newton’s method to efficiently solve the nonconvex MINLP model with separable concave terms and mixed-integer fractional terms in the objective functions.

2.3 Multi Period Models

One of the decisions researchers have to make when constructing their model is that whether the model will be run for a single or multiple time periods. As it is evident, a multi period model is more realistic than a single period one. However, incorporation of multiple periods incurs a computational burden on the model. The nature of the supply chain also plays a role in this decision making process. Depending on the configuration, feedstock, and etc. it may be concluded that the assumption of having a single period does not affect the optimal decisions drastically. In other words, there should be tradeoff between the added computational complexity and the necessity having multiple time periods. Out of 146 papers gathered by Ghaderi et al. (2016), 71 articles have a single time period and 74 have considered multiple periods but a trend can be observed indicating that the number of models with multiple time periods is meaningfully higher than the single period in the last five years.

Several number of our selected articles have included multiple time periods in their models (An et al., 2011; Azadeh et al., 2014; You & Wang, 2011; Zhang et al., 2013; Shama et al., 2013; You et al., 2012; Gonela et al., 2015; Azadeh & Arani, 2016; Bairamzadeh et al., 2015; Babazadeh et al., 2015; Santibañez-Aguilar et al., 2016; Cambero & Sowlati, 2016; Mohseni et al., 2016; Ahn et al., 2015).

What follows is some examples of the reasons that articles have considered multiple time periods. An, Wilhelm and Searcy (2011) proposed a time-staged model as their model is deterministic and they have switchgrass as their feedstock. Swithgrass has an approximate yield period of 8 years with the first two years requiring investment while the remaining years do not. Azadeh et al. (2014) developed a multi period planning framework although their model incorporates uncertainties since they had multiple feedstock and wanted to take into account shortage in different periods and observe its impact on the optimal decisions. You and Wang (2011) also considered multiple periods for their model and parameters since it is a deterministic one in this research. Zhang et al. (2013) have considered multiple periods to account for different demands, inventory, and production levels. Sharma et al. (2013) used monthly time intervals to take into account different weather scenarios affecting the biomass yield. You et al. (2012) have used multiple time periods for weather factor, biofuel demand, inventory levels, harvesting, and etc.; Gonela et al. for inventory capacity, selling and production price, biomass yield, etc.; Azadeh and Arani for (2016) for available biomass, demand, prices, shortage cost, etc.; Bairamzadeh et al. for (2015) for demand, inventory, biomass harvest, etc.; Santibañez-Aguilar et al. for (2016) for biomass yield and storage and demand; Cambero and Sowlati (2016) for their social, economic, and environmental parameters; Mohseni et al. (2016) for available resources, biomass yield, pipe line capacity, fertilizer price, and etc. Ahn et al. (2015) developed a multi-period model of the strategies to manage a biodiesel supply chain to determine the system configuration that is most effective when the amount and locations of biodiesel demand change with time. Babazadeh et al. (2015) have multiple periods because Rentizelas et al. (2009) stated that feedstock for bioenergy production are available in specific time periods and therefore integration and optimization of bioenergy supply chain should be performed under multi-period conditions.

Kim, Realff and Lee (2011) also utilized multiple time periods but they took this feature into consideration not in the model but in the sensitivity analysis part of the research.

2.4 Multi Objective Models

Most of the optimization models comprise of a single objective function while in reality multiple criterion for decision making might be considered. In the BSCND literature 117 articles have been published with a single objective (80%); and 29 with multiple objectives (20%). The main objective in designing and planning a biofuel supply chain is for it be cost competitive. However, the fact that a major incentive of biofuel production is alleviating the environmental problems should not be neglected. Figure 5 shows the different objectives of the literature and their popularity.

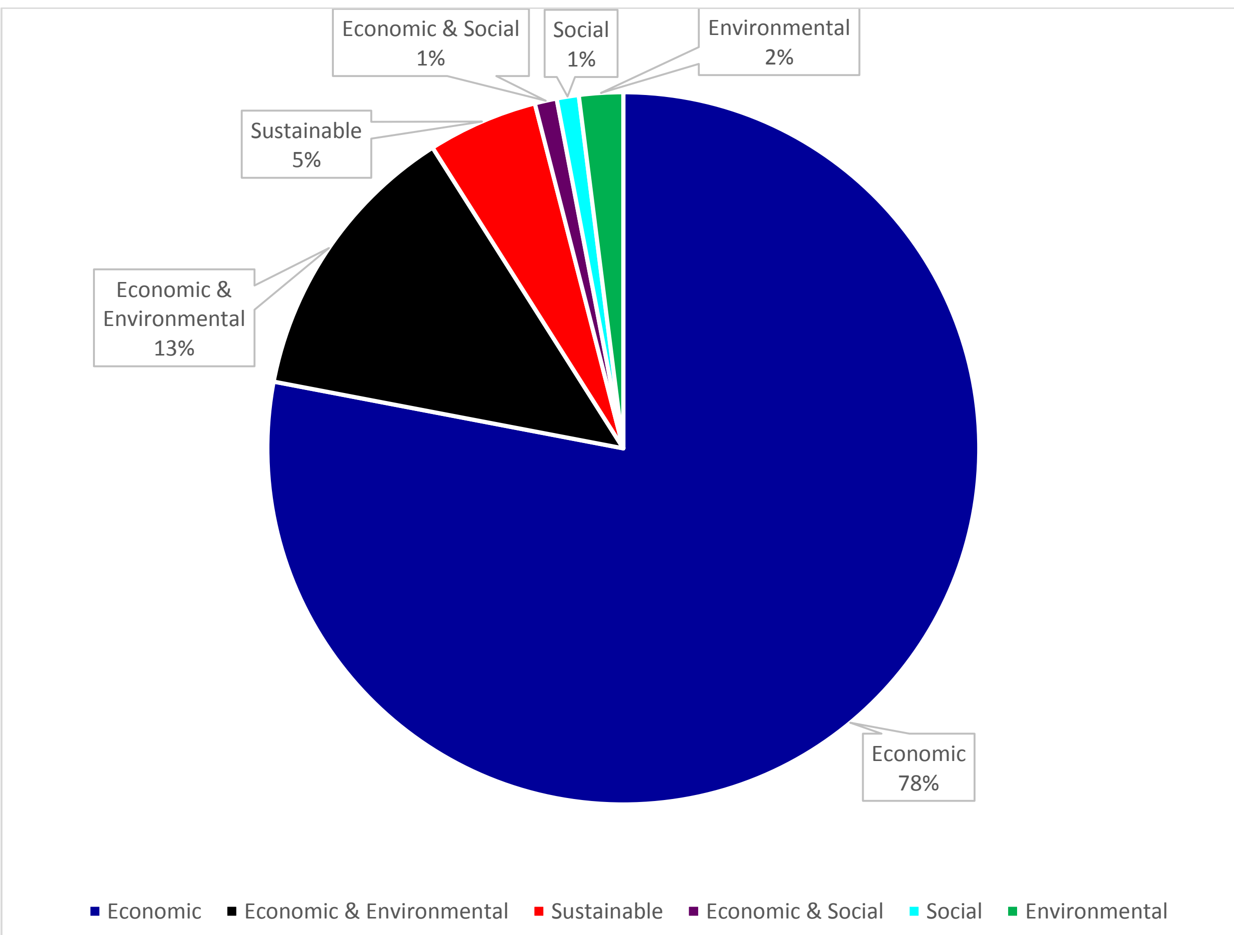


Figure 5: Popularity of different objectives (Ghaderi et al., 2016)

Some of the selected articles summarized have modeled the problems with multiple objectives (Liu et al., 2014; Tong et al., 2014; You & Wang, 2011; You et al., 2012; Bairamzadeh et al., 2015; Santibañez-Aguilar et al., 2016; Cambero & Sowlati, 2016; Gong & You, 2014). The objectives of these articles and their solution method in terms of the model being multi-objective will be further discussed.

Liu, Qiu, and Chen (2014) proposed a model with three objectives. An economic objective, an energy objective, and an environmental one. The model was solved by ε-Constraint method and a Pareto-optimal solution surface was obtained. The model maximizes and minimizes the total energy yield and Green House Gas (GHG) emission, respectively in addition to the traditional cost minimization. Tong et al. (2014) multiple objectives are total and unit cost minimization and the unit cost minimization is believed to make the final product more cost competitive. These two objectives are not competing ones and hence methods such as ε-Constraint have not been utilized. You and Wang (2011) considered the minimization of GHG emission in addition to the total annualized cost. Their multi-objective optimization problem was also solved with the ε-constraint method and their Pareto-optimals show the different combinations of optimal annualized cost _biomass processing, and fuel production network structures_ with the environmental performance of the biomass-to-liquids supply chain. You et al. (2012) have optimized their model under economic, environmental, and social objectives. The economic objective is measured by the total annualized cost; the environmental one by the life cycle greenhouse gas emissions; and the social one is with the number of created local jobs. This multi-objective MILP problem is also solved with an ε-Constraint method with the Pareto-optimal illustrating the tradeoff between the economic, environmental, and social dimensions of the problem. Bairamzadeh et al. (2015) have considered three objectives, namely, total profit maximization, number of jobs maximization, and environmental impact minimization. Eco-indicator 99_a well-known environmental impact assessment method based on life-cycle-assessment_ was used for the estimation of the relevant environmental impacts as one of the objectives. ε-Constraint is the solution method of choice in this article. Santibañez-Aguilar et al. (2016) have modeled their problem with two objectives. Maximize (total) profit and minimize environmental impact. The environmental impact of this article was also measured via the Eco-indicator 99. This article has similarly employed ε-Constraint to solve the problem. The objectives of Cambero and Sowlati (2016) are the social benefit, net present value, and greenhouse gas emission saving potential which are optimized using the ε-Constraint method. Gong and You (2014) developed a model to simultaneously optimize the unit cost and the unit Global Warming Potential (GWP). Two Pareto-optimal curves were obtained. First one for biofuel production illustrating a tradeoff between production cost and GWP and the second for biological carbon sequestration illustrating a tradeoff between sequestration cost and GWP.

2.5 Models Incorporating Uncertainty

Uncertainty is an inherent part of biofuel supply chains as parameters like biomass yield are heavily dependent on fickle weather; demand on volatile economy; etc. These uncertainties can turn an optimal solution to a sub-optimal one or even change the feasibility of the problem. Ghaderi et al. (2016) analysis of literature shows that approximately only 20% percent of articles of BSCND have considered uncertainties of parameters and it is also observed that these articles have all been published since 2010. Furthermore, parameters pertaining to biomass supply and biofuel demand constitute 55% of considered non-deterministic parameters.

What follows is the discussion of our selected articles that have incorporated uncertainty, their uncertain parameters and methods (Awudu & Zhang, 2013; Azadeh et al., 2014; Kim et al., 2011a, b; Osmani & Zhang, 2013; Tong et al., 2014; Ren et al., 2015; Sharma et al., 2013; Foo et al., 2013; Chen & fan, 2012; Gonela et al., 2015; Azadeh & Arani, 2016; Bairamzadeh et al., 2015; Santibañez-Aguilar et al., 2016; Mohseni et al., 2016).

Awudu and Zhang (2013) incorporated the uncertainty of final product demand and price in their model by a stochastic production planning. This research is a follow up research of a previous work by Zhang et al. (2013) which did not incorporate uncertainty. The uncertain model is more robust than the deterministic one. Azadeh et al. (2014) proposed a different approach named scenario-based robust optimization to incorporate uncertainty in the same parameters of final product as the previous work. They concluded that this model is more realistic as it has captured more characteristics of a real world supply chain. Kim et al. (2011a) utilized a scenario-based stochastic model where 33 scenarios were created for different combinations of biomass availability, maximum demand, sale price of final products, and yield of intermediate and final products. The uncertainty incorporation was done in the sensitivity analysis part of the article not the model. That is, solving each scenario by the model and then comparing the results. They concluded that the multiple scenario design mitigates the impact of variation on the supply chain. Kim et al. (2011b) have only biomass availability, biofuel demand, and price as uncertain parameters and mention the need for capturing the important uncertainties in future works. Osmani and Zhang (2013) used stochastic optimization with 1000 scenarios which were the combinations of three parameters each with 10 levels. They concluded that their model can cope with uncertainty of switchgrass yield and final product parameters and still result in the optimal configuration of supply chain given the real world variations. Tong, You and Rong (2014) developed a robust model using robust formulation of Bertsimas-Sim to take into account uncertainties in both supply and demand side. It is concluded that the robust model results in the optimal decisions in different scenarios. Ren et al. (2015) considered costs, prices, demand of markets, quantity of seed, fertilizer, pesticide, yield of grain, etc. uncertain and used interval linear programming to incorporates them in the model and solve it. Sharma et al. (2013) utilized scenario optimization modeling approach for incorporating the uncertainty in the number of harvesting workdays and weather. The scenarios where constructed using monthly time intervals to reflect the weather. Foo et al. (2013) developed multiple planning scenarios to reflect uncertainties in biomass supply which are business decisions or the long-term effects of climate change on agricultural productivity. Their robust model incorporates a set of constraints for each anticipated scenario, ensuring the ability of solution identified to satisfy operational requirements no matter which scenario is realized. Chen and Fan (2012) developed a standard two-stage stochastic programming paradigm based on the “non-anticipativity” concept of Rockafellar and Wets (1991) meaning that since the future scenario is not known when planning decision is made the first-stage (planning) makes the decision before the actual realization of system uncertainties then the second-stage takes corrective measures against any infeasibility or sub-optimality corollary to a particular uncertainty realization if necessary. Stochastic programming has been used by Gonela et al. (2015) to capture selling price and demand of bioethanol, yield rate of first and second generation biomass uncertainties. Azadeh and Arani (2016) incorporated uncertainties of available biomass and demand in both steps of their model meaning system dynamics model alongside the mathematical model by a scenario-based modeling. In each scenario, links between biomass fields, biorefineries, consumption markets, and biomass fields themselves were disrupted. Bairamzadeh et al. (2015) considered uncertainties in market prices, biofuel demands, and environmental impacts which are treated as fuzzy values and dealt with them with a robust possibilistic programming approach. Santibañez-Aguilar et al. (2016) proposed a method in which uncertainty is incorporated by the stochastic generation of scenarios using the Latin Hypercube method that constructs experiments for the Monte-Carlo method. Each single scenario is solved by a deterministic optimization model to select the more robust supply chain relying on statistical data involved. The uncertainties were considered in the raw material price. Mohseni et al. (2016) utilized a robust optimization method ensuring that strategic and tactical supply chain decisions remain optimal for almost all possible realizations of the uncertain parameters.

2.6 Gap analysis

- As discussed earlier, disadvantages of first generation biomass lead to researches being conducted for second and third generation. The third generation of biomass especially need to be investigated so that their potential is assessed. A gap exists in the BSCDN literature as only three articles focusing on the third generation of biofuels have been published.

- Construction of the BSC model with the incorporation of multiple periods is becoming a trend in BSCND literature and this gap is being closed although it still exists.
- Incorporation of uncertainty is another gap in the literature indicated by only 20% non-deterministic models. In addition, most of these non-deterministic models use scenario based stochastic method which becomes computationally complex for robustness against all possible realizations.
- Multi-objective models comprise 20% of the literature. This could be looked upon as a gap in the literature since there are other criteria like the ones mentioned in the subsection 2.4 that should be considered other than economic criterion.

3. Methodology

This section describes and presents the proposed model of this study based on the literature gaps and the previous sections.

First, the process of biofuel production from microalgae is explained as it is a prerequisite for BSCND. Then the mathematical model which represents a tailored version of this process for the described problem is presented.

3.1 Microalgae-to-Biofuel Process

The process by which microalgae is turned into biofuel consists of five levels: (1) Cultivation, (2) Harvesting, (3) Drying, (4) Lipid extraction, and (5) Conversion (Delrue, Setier, Sahut, Cournac, Roubaud, Peltier, and Froment 2012). Figure 6 adapted from Delrue et al. (2012) depicts these levels and introduces some of the available technologies of each sub-processes that will be further discussed.

3.1.1 Cultivation

Microalgae need raw materials such as water, CO_2, sun light, and nutrients to grow. Microalgae need for the aforementioned raw materials is less than other biomass due to their single-celled structure. Nitrogen and Phosphorous are the essential nutrients required for algae growth which can be provided by traditional fertilizers. Where algae are grown is the next question that needs

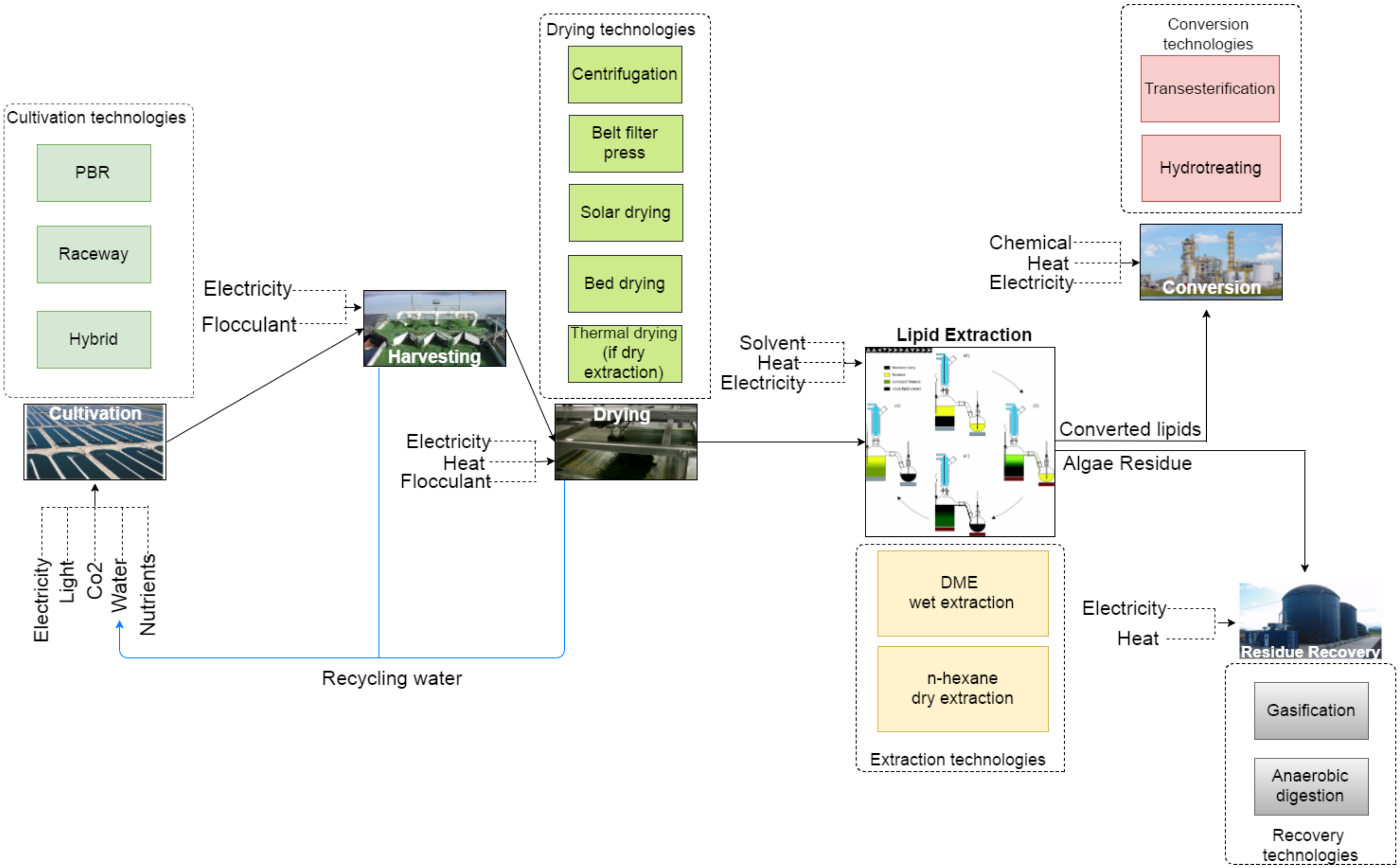


Figure 6: Microalgae-to-Biofuel process

to be answered in cultivation phase. There are two types cultivation systems: (1) Open ponds and (2) Photobioreactors

1. Open pond systems:

Operation and foundation of open ponds is easier and cheaper than photobioreactors. Open pond systems can be classified into three major categories despite their numerous configurations in terms of shape, dimensions, etc.: (1) Unmixed, (2) Circular, and (3) Raceway (Lundquist, Woertz, Quinn, and Benemann 2010). The unmixed ponds are deemed inefficient as there is no water or CO_2 flow meaning that only the surface algae receive sunlight and CO_2. Circular ponds with the surface area of approximately 1000 m^2 utilize central motors for rotation of water. Raceway ponds are canals with 50 cm depth and 1 m width. Rotational pumps were implemented at the starting point of these ponds. This structure was first devised by University of California, Berkeley. Raceway ponds are capable of being built in a larger scale but have less water flow speed. However, in the evolution of raceway ponds, pedal motors were utilized in the middle of the canals improving their efficiency. Raceway ponds are currently the prevalent cultivation technology in the world and their evolution continues with design parameter improvements. To achieve the optimal efficiency in raceway ponds, the surface should be approximately 4 ha and the depth 25-35 cm. Even though deeper ponds contain more algae but problems such as temperature difference of top and low levels, high energy demand for maintaining the flow, and CO2 injection difficulties arise. Optimal water flow speed as another important factor is believed to be 20-30 $cm * s^{-1}$. Higher speeds cost energy and lower speeds result in sedimentation (Landquisit et al., 2010; Ferrell & Sarisky-Reed, 2010)

CO_2 should be injected to the ponds as bubbles for maximum productivity. PH and Dilution rate are the other two notable factors in cultivation system efficiency. CO_2 will improve the productivity but it will it also changes the PH of water that can disrupt optimal growth (Weissman, Goebel, & Benemann 1988). Optimal dilution rate (i.e. fully grown microalgae exit rate and new microalgae enter rate) based on Pedroni, Lamenti, Prosperi, Ritorto, Scolla, Capuano, and Valdiserri (2004) research is the enter and exit rate of 20-50 percent of total pond volume.

2. Photobioreactor systems:

despite their advantages such as not being complex and having low costs, open pond systems suffer from disadvantages such as invasion of other algae strain, bacteria contamination, and CO_2 being released in the atmosphere. Photobioreactors overcome the aforementioned shortcomings of open ponds due to their closed atmosphere. Closed atmosphere, however, causes overheating in warm seasons mandating the cooling of tubes by water spray that results in more water consumption than open ponds in warm seasons. Furthermore, as CO_2 cannot escape the photobioreactors, other gases such as oxygen cannot either which means that oxygen should somehow be extracted from the system. This increases the operational costs (Weinssman et al., 1988). In conclusion, photobioreactors have higher productivity but for a considerable amount of microalgae thousands of them are required. This and high construction and maintenance costs, result in the unit price of biofuels produced by photobioreactors three-fold the price of biofuels produced by open ponds (Davis, Aden, & Pienkos, 2011).

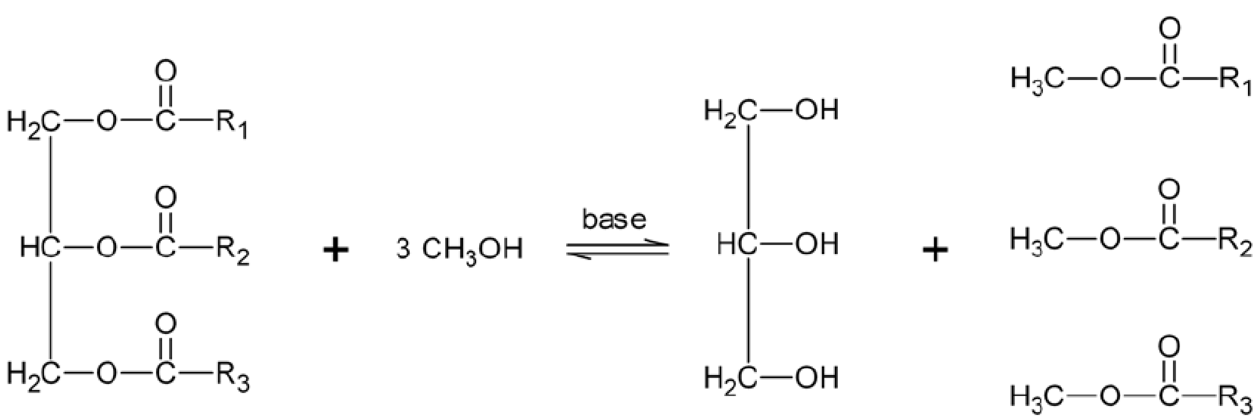
3.1.2 Harvesting and Drying

After microalgae are fully grown, they should be separated from the growth culture. Regardless of cultivation technology, density of microalgae in the growth media is very low and about 0.1-0.4 g*L^{-1} (Chisti, 2007). In order for the lipid to be extracted, algae density should be at least 150 g*L^{-1} or 15%. Hence, water should be separated from the media as much as possible and then biomass should be further dried for higher density. These processes which constitute 20% of the total biofuel production cost are among the important obstacles hindering the development of algal biofuel industry. This 20% is due to the fact that these processes are energy intensive and require expensive raw materials. Chemical and auto flocculation methods are used in harvesting which force algae to form lumps (Barros, Gonçalves, Simões, & Pires, 2015).

After harvesting biomass density should further increase for better efficiency in the lipid extraction level. Drying methods are the answer to this need. Some of drying technologies are depicted in figure 6.

3.1.3 Lipid extraction and conversion

After the drying process, biomass can be converted to different fuels by different processes. Microalgae can be converted to ethanol via fermentation since they contain sugars. However, micro-algal oil which can be used to produce biodiesel appeals more to the industry nowadays. This is due to the microalgae ability to store considerable amounts of lipid in their cells. Lipid extraction technologies mentioned in Figure 6 are chosen based on previous and proceeding processes along with other criteria such as cost, required raw material, etc. For biodiesel production triglycerides of algal oil chemically react with methanol in a reaction called Alcoholysis or Transesterification. This reaction produces methyl ester (biodiesel) and glycerol. It should be noted that this reaction occurs in multiple levels: first triglycerides are converted to diglycerides and then monoglycerides and finally glycerol (Chisti, 2007). Figure 7 illustrates the Transesterification reaction.



Triglyceride Methanol Glycerol Methyl Esters

Figure 7: Transesterification process

The reaction is catalyzed by acidic, alkaline, and lipase enzyme catalysts. Alkaline catalysts are 4000 times more effective than acidic ones and are hence usually used as the commercial catalysts. Lipase enzyme catalysts offer advantages which are outweighed by their high cost (Fukuda, Kondo, & Noda 2001).

Algae residue after lipid extraction can be used in several different ways. The residue can be used as animal feed since it contains considerable amounts of protein (around 20%). Algae residue can also be used in Anaerobic digestion or Gasification processes to produce electricity, heat, and biogas.

3.2 Deterministic Mathematical Model

This section presents the mathematical model of described problem. Indices, parameters, and decision variables are first defined and then the objective and constraints are presented and explained.

Indices

o	Index of CO_2 sources
f	Index of fresh water sources
w	Index of waste water sources
k	Index of brackish water sources
n	Index of nitrogen sources
h	Index of phosphorus sources

r	Index of other raw material types
s_r	Index of sources of raw material type r
l	Index of possible locations for biorefineries
p	Index of production pathways at biorefineries
y	Index of biodiesel types
c	Index of capacity options for biorefineries
g	Index of consumption market of glycerin
b	Index of consumption market of biodiesel
t	Index of time stages

Parameters

ao_o^t	Available CO_2 at source o at time stage t
af_f^t	Available fresh water at source f at time stage t
aw_w^t	Available waste water at source w at time stage t
ak_k^t	Available brackish water at source k at time stage t
an_n^t	Available nitrogen at source n at time stage t
ah_h^t	Available phosphorus at source h at time stage t
$ar_{s_r}^t$	Available raw material type r at source s_r at time stage t
$\widetilde{to}_{o,l}$	Purchase and Transportation cost of CO_2 from source O to biorefineries l
$\widetilde{tf}_{f,l}$	Purchase and Transportation cost of fresh water from source f to biorefineries l

$\widetilde{tw}_{w,l}$	Purchase and Transportation cost of waste water from source w to biorefineries l
$\widetilde{tk}_{k,l}$	Purchase and Transportation cost of brackish water from source k to biorefineries l
$\widetilde{tn}_{n,l}$	Purchase and Transportation cost of nitrogen from source n to biorefineries l
$\widetilde{th}_{h,l}$	Purchase and Transportation cost of phosphorus from source h to biorefineries l
$\widetilde{tr}_{r,l}$	Purchase and Transportation cost of raw material type r from source s_r to biorefineries l
$\widetilde{tg}_{l,g}$	Transportation cost of glycerin from biorefineries l to market g
$\widetilde{tb}_{l,b}$	Transportation cost of biodiesel from biorefineries l to market b
$\widetilde{cc}_{l,p,c}^{t}$	Annualized capital cost of biorefinery l with production pathway p and capacity option c at time stage t
$\widetilde{pc}_{y,l,p}^{t}$	Unit production cost of biodiesel type y at biorefinery l with production pathway p at time stage t
$\widetilde{hb}_{y,l}$	Unit inventory holding cost of biodiesel type y at biorefinery l
$\widetilde{hg}_{l}$	Unit inventory holding cost of glycerin at biorefinery l
$\gamma_l^t = yy_l^t$	Biomass productivity per unit area at location l at time stage t
$rm_{r,y,p}$	Requirement of raw material type r to produce biodiesel type y by pathway p

$cb_{y,p}$	Conversion rate of biomass to biodiesel type y under production pathway p
cg_p	Conversion rate of biomass to glycerin under production pathway p
$\varphi_c = qq_c$	Surface area of ponds of biorefinery with capacity option c
db_b^t	Demand for biodiesel at market b at time stage t
dg_g^t	Maximum amount of glycerin which can be sold at market g at time stage t
$\widetilde{pr}_r^t$	Price of raw material r at source s_r at time stage t
$\widetilde{pb}_{y,b}^t$	Price of biodiesel type y at market b at time stage t
$\widetilde{pg}_g^t$	Price of glycerin at market g at time stage t
$sb_{y,l}$	Maximum storage capacity of biodiesel type y at biorefinery l
sg_l	Maximum storage capacity of glycerin at biorefinery l
mo	CO_2 requirement for production one unit of biomass
mw	water requirement for production one unit of biomass
mn	nitrogen requirement for production one unit of biomass
mh	phosphorus requirement for production one unit of biomass
na	Amount of nitrogen available per unit of waste water
ha	Amount of phosphorus available per unit of waste water
$m_{r,p}$	raw material r requirement for processing one unit of biomass by production pathway p

$\widetilde{GC}_{o,l}$ GHG emissions of production and transporting one unit of CO_2 from source o to biorefinery l

$\widetilde{GF}_{f,l}$ GHG emissions of production and transporting one unit of fresh water from source f to biorefinery l

$\widetilde{GW}_{w,l}$ GHG emissions of production and transporting one unit of waste water from source w to biorefinery l

$\widetilde{GK}_{k,l}$ GHG emissions of production and transporting one unit of brackish water from source k to biorefinery l

$\widetilde{GN}_{n,l}$ GHG emissions of production and transporting one unit of nitrogen from source n to biorefinery l

$\widetilde{GH}_{h,l}$ GHG emissions of production and transporting one unit of phosphorus from source h to biorefinery l

$\widetilde{GR}_{s_r l}$ GHG emissions of production and transporting one unit of raw material r from source s_r to biorefinery l

$\widetilde{GE}_{l,p,c}$ GHG emissions of establishing biorefinery l with production pathway p and capacity c

$\widetilde{GP}_l$ GHG emissions per unit quantity of biomass cultivated at biorefinery l at time stage t

$\widetilde{GS}$ GHG emissions of storing unit quantity of biodiesel at biorefinery l

$\widetilde{GG}$ GHG emissions of storing unit quantity of glycerin at biorefinery l

$\widetilde{GB}_{y,p}$ GHG emissions of producing unit quantity of biodiesel using production pathway p

$\widetilde{G2}_{l,g}$ GHG emissions of transporting one unit of glycerin from biorefinery l to market g

$\widetilde{G3}_{l,b}$ GHG emissions of transporting one unit of biodiesel from biorefinery l to market b

Decision variables

$xo_{o,l}^{t}$ Flow of CO_2 from source o to biorefinery l at time stage t

$xf_{f,l}^{t}$ Flow of fresh water from source f to biorefinery l at time stage t

$xw_{w,l}^{t}$ Flow of waste water from source w to biorefinery l at time stage t

$xk_{k,l}^{t}$ Flow of brackish water from source k to biorefinery l at time stage t

$xn_{n,l}^{t}$ Flow of nitrogen from source n to biorefinery l at time stage t

$xh_{h,l}^{t}$ Flow of phosphorous from source h to biorefinery l at time stage t

$xr_{s_r,l}^{t}$ Flow of raw material r from source s_r to biorefinery l at time stage t

$xb_{y,p,l,b}^{t}$ Flow of biodiesel type y from biorefinery l with production pathway p to market b at time stage t

$xg_{l,g}^{t}$ Flow of glycerin from biorefinery l to market g at time stage t

$ib_{y,l}^{t}$ Inventory level of biodiesel type y at location l at time stage t

ig_{l}^{t} Inventory level of glycerin at location l at time stage t

$U_{l,p,c}^{t}$ 1 if a biorefinery with capacity c and production pathway p is opened at location l at time stage t; 0 otherwise

ZF_l 1 if fresh water is chosen for biorefinery l; 0 otherwise

Zk_l 1 if brackish water is chosen for biorefinery l; 0 otherwise

The size of the problem is |o|*|f|*|w|*|k|*|n|*|h|*|r|*|s|*|l|*|p|*|y|*|c|*|g|*|b|*|t| which equals 10*10*10*10*10*10*3*10*15*5*2*3*10*10*4.

The parameters marked with tilde are the parameters that will be considered uncertain in the non-deterministic model.

Objective functions:

- Economic objective function:

Equation (1) is the economic objective function which maximizes the expected profit (revenue – cost) throughout the entire planning horizon. The different components of Equation (1) respectively refer to the: (1) revenue from the sale of biodiesel; (2) revenue from the sale of glycerin; (3) procurement and transportation cost of CO_2; (4) procurement and transportation cost of fresh water; (5) procurement and transportation cost of waste water; (6) procurement and transportation cost of brackish water; (7) procurement and transportation cost of nitrogen; (8) procurement and transportation cost of phosphorus; (9) procurement and transportation cost of other raw materials; (10) biodiesel transportation cost; (11) glycerin transportation cost; (12) capital cost of biorefineries; (13) production cost of biodiesel; (14) inventory holding cost of glycerin and (15) inventory holding cost of biodiesel.

$$Max\ Profit = \sum_y \sum_b \sum_t \sum_p \sum_l pb_{y,b}^t xb_{y,p,l,b}^t + \sum_l \sum_g \sum_t pg_g^t xg_{l,g}^t \tag{1}$$
$$- \sum_o \sum_l \sum_t to_{O,l} xo_{o,l}^t - \sum_f \sum_l \sum_t tf_{f,l} xf_{f,l}^t$$
$$- \sum_w \sum_l \sum_t tw_{w,l} xw_{w,l}^t - \sum_k \sum_l \sum_t tk_{k,l} xr_{k,l}^t$$
$$- \sum_n \sum_l \sum_t tn_{n,l} xn_{n,l}^t - \sum_h \sum_l \sum_t th_{h,l} xh_{h,l}^t$$
$$- \sum_{s_r} \sum_l \sum_t tr_{s_r,l} xr_{s_r,l}^t - \sum_l \sum_b \sum_y \sum_p \sum_t tb_{l,b} xb_{y,p,l,b}^t$$
$$- \sum_l \sum_g \sum_t tg_{l,g} xg_{l,g}^t - \sum_l \sum_p \sum_c \sum_t cc_{l,p,c}^t\, U_{l,p,c}^t$$
$$- \sum_y \sum_l \sum_p \sum_b \sum_t pc_{y,l,p}^t xb_{y,p,l,b}^t - \sum_l \sum_t hg_l ig_l^t$$
$$- \sum_y \sum_l \sum_t hb_{y,l} ib_{y,l}^t$$

- Environmental objective function:

Equation (2) is the environmental objective function which minimizes total CO_2-equivalent GHG emission caused by supply chain operations. The different components of Equation (2) respectively represent the: (1) GHG emissions of CO_2; (2) GHG emissions of fresh water; (3) GHG emissions of waste water; (4) GHG emissions of brackish water; (5) GHG emissions of

$$
\begin{aligned}
Min\ GHG = & \sum_{o}\sum_{l}\sum_{t} GO_{O,l} xo_{o,l}^{t} + \sum_{f}\sum_{l}\sum_{t} GF_{f,l} xf_{f,l}^{t} \\
& + \sum_{w}\sum_{l}\sum_{t} GW_{w,l} xw_{w,l}^{t} + \sum_{k}\sum_{l}\sum_{t} GK_{k,l} xr_{k,l}^{t} \\
& + \sum_{n}\sum_{l}\sum_{t} GN_{n,l} xn_{n,l}^{t} + \sum_{h}\sum_{l}\sum_{t} GH_{h,l} xh_{h,l}^{t} \\
& + \sum_{s_r}\sum_{l}\sum_{t} GR_{s_r,l} xr_{s_r,l}^{t} + \sum_{l}\sum_{p}\sum_{c}\sum_{t} GE_{l,p,c} U_{l,p,c}^{t} \\
& + \sum_{l}\sum_{p}\sum_{c}\sum_{t} GP_{l,t} \gamma_{l}^{t} \varphi_{c} U_{l,p,c}^{t} + \sum_{l}\sum_{t} GG_{l} ig_{l}^{t} \\
& + \sum_{l}\sum_{y}\sum_{t} GS_{l} ib_{y,l}^{t} + \sum_{y}\sum_{p}\sum_{l}\sum_{b}\sum_{t} GB_{y,p} xb_{y,p,l,b}^{t} \\
& + \sum_{l}\sum_{g}\sum_{t} G2_{l,g} xg_{l,g}^{t} + \sum_{y}\sum_{l}\sum_{b}\sum_{p}\sum_{t} G3_{l,b} xb_{y,p,l,b}^{t}
\end{aligned}
\tag{2}
$$

nitrogen; (6) GHG emissions of phosphorus; (7) GHG emissions of other raw materials; (8) GHG emissions of establishing biorefineries; (9) GHG emissions released from open ponds during microalgae growth; (10) GHG emissions of storing glycerin; (11) GHG emissions of storing biodiesel; (12) GHG emissions of producing biodiesel; (13) GHG emissions of raw material transportation; (14) GHG emissions of glycerin transportation and (15) GHG emissions of biodiesel transportation.

Constraints:

$$ao_o^t \geq \sum_l xo_{o,l}^t \quad \forall o, t \tag{3}$$

$$af_f^t \geq \sum_l xf_{f,l}^t \quad \forall f, t \tag{4}$$

$$aw_w^t \geq \sum_l xw_{w,l}^t \quad \forall w, t \tag{5}$$

$$ak_k^t \geq \sum_l xk_{k,l}^t \quad \forall k, t \tag{6}$$

$$an_n^t \geq \sum_l xn_{n,l}^t \quad \forall n, t \tag{7}$$

$$ah_h^t \geq \sum_l xh_{h,l}^t \quad \forall h, t \tag{8}$$

$$ar_{s_r}^t \geq \sum_l xr_{s_r,l}^t \quad \forall s_r, t \tag{9}$$

$$\sum_o xo_{o,l}^t \geq \sum_p \sum_c \gamma_l^t \varphi_c U_{l,p,c}^t mo \quad \forall l, t \tag{10}$$

$$\sum_f xf_{f,l}^t + \sum_w xw_{w,l}^t + \sum_k xk_{k,l}^t \geq \sum_p \sum_c \gamma_l^t \varphi_c U_{l,p,c}^t mw \quad \forall l, t \tag{11}$$

$$\sum_f \sum_t xf_{f,l}^t \leq M * ZF_l \quad \forall l \tag{12}$$

$$\sum_k \sum_t xk_{k,l}^t \leq M * ZK_l \quad \forall l \tag{13}$$

$$ZF_l + ZK_l \leq 1 \quad \forall l \tag{14}$$

$$\sum_{w} xw_{w,l}^{t}na + \sum_{n} xn_{n,l}^{t} \geq \sum_{p}\sum_{c} \gamma_l^t \varphi_c U_{l,p,c}^{t} mn \quad \forall l,t \tag{15}$$

$$\sum_{w} xw_{w,l}^{t}ha + \sum_{h} xh_{h,l}^{t} \geq \sum_{p}\sum_{c} \gamma_l^t \varphi_c U_{l,p,c}^{t} mh \quad \forall l,t \tag{16}$$

$$\sum_{s_r} xr_{s_r,l}^{t} \geq \sum_{p}\sum_{c} \gamma_l^t \varphi_c U_{l,p,c}^{t} m_{r,p} \quad \forall l,r,t \tag{17}$$

$$\sum_{c} \gamma_l^t \varphi_c U_{l,p,c}^{t} cb_{y,p} + ib_{y,l}^{t-1} \geq \sum_{b} xb_{y,p,l,b}^{t} + ib_{y,l}^{t} \quad \forall l,t,p,y \tag{18}$$

$$\sum_{c}\sum_{p} \gamma_l^t \varphi_c U_{l,p,c}^{t} cg_p + ig_l^{t-1} \geq \sum_{g} xg_{l,g}^{t} + ig_l^{t} \quad \forall l,t \tag{19}$$

$$\sum_{p}\sum_{c} U_{l,p,c}^{t} \leq 1 \quad \forall l,t \tag{20}$$

$$U_{l,p,c}^{t-1} \leq U_{l,p,c}^{t} \quad \forall l,p,c,t \tag{21}$$

$$ib_{y,l}^{t} \leq sb_{y,l} \quad \forall y,l,t \tag{22}$$

$$ig_l^{t} \leq sg_l \quad \forall l,t \tag{23}$$

$$\sum_{y}\sum_{p}\sum_{l} xb_{y,p,l,b}^{t} = db_b^t \quad \forall b,t \tag{24}$$

$$\sum_{l} xg_{l,g}^{t} \leq dg_g^t \quad \forall g,t \tag{25}$$

Constraint sets (3)-(9) state that in each raw material source, the amount of raw material sent to biorefineries should not exceed the maximum raw material that can be obtained from that source.

Constraint set (10) ensures that during each time stage, the amount of CO_2 sent to biorefinery l (if built ($U_{l,p,c}^{t} = 1$)) is greater than CO_2 requirement which is equal to the produced biomass ($\gamma_l^t \varphi_c$) multiplied by CO_2 requirement per unit.

Constraint set (11) shows the water requirement at each biorefinery and time period is satisfied by fresh, waste and brackish water transported. Since only one of the fresh water and brackish water algae species can be used in cultivation unit, constraint sets (12)-(14) ensures fresh water and brackish water are not transported to a biorefinery simultaneously.

Constraint sets (15) and (16) ensure the required amount of nitrogen and phosphorus for each biorefinery are provided through waste water nutrients and nitrogen and phosphorus fertilizers.

Constraint set (17) satisfies the need of other raw materials.

Constraint set (18) ensures that for each biorefinery, the total amount of biodiesel shipped to all markets at time period t plus the biodiesel inventory at the end of time period t is not greater than the maximum amount of biodiesel that can be produced at time period t (equals to total cultivated biomass $\gamma_l^t \varphi_c$ multiplied by conversion rate $cb_{y,p}$) plus the biodiesel inventory at the end of previous time period.

A similar condition is held for the production and storage of glycerin, which is given by constraint set (19).

Constraint set (20) ensures that at most one type of production pathway and capacity level can be assigned to each biorefinery.

Constraint set (21) shows that if biorefinery l is opened at current time period, it cannot be shut down at a later time period.

Constraint sets (22) and (23) enforce an upper bound on the total amount of biodiesel and glycerin stored during time period t at biorefinery l.

Constraint set (24) ensures that the amount of biodiesel shipped from all biorefineries to each demand zone b is equal to its biodiesel requirement.

Constraint set (25) ensures that the amount of glycerin sent to each demand zone g is not greater than the maximum amount of glycerin which can be sold at that zone.

3.3 Robust Optimization

As mentioned previously, many aspects of algal biofuel supply chains are plagued with uncertainties. This is due to the fact that parameters such as biomass yield and oil content, demand of product, supply of raw materials, and prices, GHG emissions, and transportation costs are functions of factors such as weather, economy, accuracy of research, and status of other industries which are uncertain in nature. There are different approaches to incorporation of uncertainty. Stochastic programing is the prevalent approach of capturing the uncertainties of supply chain environment (Klibi, Martel, & Guitouni, 2010). This is due to the fact that stochastic programming is a powerful tool to incorporate uncertainty. However, it has its weaknesses, too. As an example, stochastic programming requires determination of the distribution of uncertain parameters which is a challenging task as it needs well collected and reliable historical data. Furthermore, scenario based stochastic programing which does not require large historical data sets and is popular in the SCND literature, should incorporate many scenarios to satisfactorily model the uncertainties and often results in computational intractability (Pishvaee, Rabbani, & Torabi, 2011). Robust optimization as another uncertainty incorporation approach, overcomes the shortcomings of stochastic programming as it needs the lower and upper bound of uncertain parameters as opposed to their distribution and also preserves the computational tractability of the original model. Soyster (1973) first introduced the concept of robust optimization. In this pessimistic robust approach, all of the uncertain parameters attain their worst-case scenario values which is unrealistically over conservative. Afterwards, El Ghaoui, Oustry, and Lebret (1998) and Ben-Tal, and Nemirovski (2000) made a meaningful contribution to the robust optimization literature by devising a robust counterpart formulation under ellipsoid uncertainty set which grants the control of conservatism level to the decision maker. Bertsimas & Sim (2004) further developed the robust optimization approach by preserving the class of the nominal problem and also enabling full control of the conservatism degree. Due to the aforementioned advantages of Bertsimas & Sim (2004) robust method, this method has been adopted in this work to take the uncertainties of the supply chain into consideration. The Bertsimas and Sim robust method will be explained in the following and final part of this section (Mohseni et al., 2016; Bertsimas & Sim, 2004).

The following LP example will be used to demonstrate this approach:

$$\begin{aligned} &\text{M}in \quad cx \\ &s.t: \sum_j \tilde{a}_{ij}\, x_j \geq b_i \quad \forall i \\ &\qquad x \in X \end{aligned} \tag{26}$$

Here coefficients $\tilde{a}_{ij}$ are the uncertain parameters. Let J_i represent the set of uncertain coefficients of row i. Each coefficient $\tilde{a}_{ij}$ is considered as a random variable which takes values in the interval $[a_{ij} - \hat{a}_{ij}, a_{ij} + \hat{a}_{ij}]$, and a_{ij} and $\hat{a}_{ij}$ respectively represent the nominal value and the variation amplitude of the uncertain parameter. A parameter Γ_i, called uncertainty budget, is introduced for each constraint i, to control the trade-off between the robustness of the model and the conservatism level of the solution. Parameter Γ_i, which is not necessarily an integer, takes values from $[0, |j_i|]$, where $|j_i|$ denotes the cardinality of set j_i. Parameter Γ_i forces $\lfloor \Gamma_i \rfloor$ coefficients of row i to take their worst value while shifting another coefficient (i.e., $\tilde{a}_{it_i}$) from its nominal value to its worst value by $(\Gamma_i - \lfloor \Gamma_i \rfloor)\hat{a}_{it_i}$. The robust counterpart of model (26) based on the above described method is demonstrated as the following nonlinear form:

$$\begin{aligned} &\text{M}in \quad cx \\ &s.t: \sum_j a_{ij} x_j - \max_{\{S_i \cup \{t_i\} | S_i \subseteq J_i, |S_i| = \lfloor \Gamma_i \rfloor, t_i \in J_i \backslash S_i\}} \left\{ \sum_{j \in S_i} \hat{a}_{ij}\, x_j + (\Gamma_i - \lfloor \Gamma_i \rfloor) \hat{a}_{it_i} x_j \right\} \\ &\qquad\qquad \geq b_i \quad \forall i \\ &\qquad X \geq 0 \end{aligned} \tag{27}$$

where S_i represents the coefficients that completely change and t_i shows the coefficient which changes if Γ_i is not an integer.

Given the optimal solution x_j^*, the protection function of constraint i (i.e.,

$\max_{\{S_i \cup \{t_i\}\}} \left\{ \sum_{j \in S_i} \hat{a}_{ij}\, x_j + (\Gamma_i - \lfloor \Gamma_i \rfloor) \hat{a}_{it_i} x_j \right\}$) is rewritten as the following linear programming to solve the non-linearity problem:

$$\begin{aligned} &\text{Max} \quad \sum_{j \in J_i} \hat{a}_{ij}\, |x_j^*| \eta_{ij} \\ &s.t: \quad \sum_{j \in j_i} \eta_{ij} \le \Gamma_i \\ &\qquad 0 \le \eta_{ij} \le 1 \quad \forall\, j \in j_i \end{aligned} \tag{28}$$

Problem (28) is feasible and bounded for all Γ_i. Hence, its dual pair is also feasible and bounded with the same objective value based on the strong duality theorem. Defining the dual variables λ_i and k_{ij}, the dual problem of (28) is expressed as follows:

$$\begin{aligned} &\text{Min} \quad \Gamma_i \lambda_i + \sum_{j \in J_i} k_{ij} \\ &s.t: \quad \lambda_i + k_{ij} \ge \hat{a}_{ij} \left| x_j^* \right| \quad \forall\, i, j \in j_i \\ &\qquad k_{ij} \ge 0 \quad \forall\, j \in j_i \end{aligned} \tag{29}$$

$$\lambda_i \geq 0 \quad \forall\, i$$

After substituting the formulation of (29) into (27), the linear robust counterpart is obtained as follows:

$$\begin{aligned} &\text{Min} \;\; cx \\ &\text{s.t:} \;\; \sum_j a_{ij}\, x_j - \Gamma_i \lambda_i - \sum_{j \in J_i} k_{ij} \geq b_i \quad \forall\, i \\ &\lambda_i + k_{ij} \geq \hat{a}_{ij} x_j \quad \forall\, i, j \in j_i \\ &k_{ij}, \lambda_i, x_j \geq 0 \end{aligned} \tag{30}$$

At the end, it should be mentioned that the decision makers are enabled to calibrate the conservatism and reliability level constraints by changing the budget value (Γ_i), within the range calculated as exp(-$\Gamma_i^{\,2}/2|\,j_i|$). The robust MILP model will be constructed based on the model demonstrated in section 3.2 and as described in this section.

3.4 Robust Counterpart Mathematical Model

In this section, the proposed multi objective microalgae biofuel supply chain model is extended to its robust counterpart form. As stated before, it is assumed that each uncertain parameter takes values in its corresponding perturbation range. For example, the uncertain parameter $\tilde{\varphi}$ belongs to the range $[\varphi - \hat{\varphi}, \varphi + \hat{\varphi}]$ where φ is the nominal value and $\hat{\varphi}$ is its amplitude. The cost parameters, GHG emission parameters, and the productivity parameters are the uncertain factors considered in this study which can be distinguished with tilde mark in the section 3.2 where all the parameters and decision variables are presented. With these assumptions, the robust counterpart of the objective functions and constraints are presented.

Constraints

The robust counterparts for the associated constraints of the uncertain parameters mentioned above are presented here. To develop the robust counterpart of the constraint (11), dual variables $\beta_{l,p,c}^{t}$ and $\Psi_{l.t}$ are introduced and it is reformulated as follows:

$$\sum_{f} xf_{f,l}^{t} + \sum_{w} xw_{w,l}^{t} + \sum_{k} xk_{k,l}^{t} \geq \sum_{p}\sum_{c} \delta_C \varphi_{l.t} U_{l,p,c}^{t} mw + \sum_{p}\sum_{c} \beta_{l,p,c}^{t} + \Gamma_{l.t}\Psi_{l.t} \quad \forall l,t \tag{30}$$

$$\beta_{l,p,c}^{t} + \Psi_{l.t} \geq \delta_C \hat{\varphi}_{l.t} U_{l,p,c}^{t} mw \quad \forall l,t,p,c \tag{31}$$

where $\hat{\varphi}_{l.t}$ is the amplitude of the uncertain parameter $\tilde{\varphi}_{l.t}$ and $\Gamma_{l.t}$ is the adjustable parameter which controls the conservatism level. Similarly, the robust counterparts of the constraints (15)-(19) are obtained as follows:

$$\sum_w xw_{w,l}^t na + \sum_n xn_{n,l}^t \geq \sum_p \sum_c \delta_C \varphi_{l.t} U_{l,p,c}^t mn + \sum_p \sum_c \beta 1_{l,p,c}^t + \Gamma 1_{l.t} \Psi 1_{l.t} \quad \forall l, t \tag{32}$$

$$\beta 1_{l,p,c}^t + \Gamma 1_{l.t} \Psi 1_{l.t} \geq \delta_C \hat{\varphi}_{l.t} U_{l,p,c}^t mn \quad \forall l, t, p, c \tag{33}$$

$$\sum_w xw_{w,l}^t ha + \sum_h xh_{h,l}^t \geq \sum_p \sum_c \delta_C \varphi_{l.t} U_{l,p,c}^t mh + \sum_p \sum_c \beta 2_{l,p,c}^t + \Gamma 2_{l.t} \Psi 2_{l.t} \quad \forall l, t \tag{34}$$

$$\beta 2_{l,p,c}^t + \Psi 2_{l.t} \geq \delta_C \hat{\varphi}_{l.t} U_{l,p,c}^t mh \quad \forall l, t, p, c \tag{35}$$

$$xr_{r,l}^t \geq \sum_p \sum_c \delta_C \varphi_{l.t} U_{l,p,c}^t m_{r,p} + \sum_p \sum_c \beta 3_{l,p,c}^t + \Gamma 3_{l.t} \Psi 3_{l.t} \quad \forall l, r, t \tag{36}$$

$$\beta 3_{l,p,c}^t + \Psi 3_{l.t} \geq \delta_C \hat{\varphi}_{l.t} U_{l,p,c}^t m_{r,p} \quad \forall l, r, t, p, c \tag{37}$$

$$\sum_c \delta_C \varphi_{l.t} U_{l,p,c}^t cb_{y,p} - \sum_c \beta 4_{l,p,c}^t - \Gamma 4_{l.t} \Psi 4_{l.t} + ib_{y,l}^{t-1} \geq \sum_b xb_{y,p,l,b}^t + ib_{y,l}^t \quad \forall l, t, p, y \tag{38}$$

$$\beta 4_{l,p,c}^t + \Psi 4_{l.t} \geq \delta_C \hat{\varphi}_{l.t} U_{l,p,c}^t cb_{y,p} \quad \forall l, t, p, y, c \tag{39}$$

$$\sum_{c}\sum_{p}\delta_{C}\varphi_{l.t}U_{l,p,c}^{t}cg_{p}-\sum_{p}\sum_{c}\beta 5_{l,p,c}^{t}-\Gamma 5_{l.t}\Psi 5_{l.t}+ig_{l}^{t-1} \geq \sum_{g}xg_{l,g}^{t}+ig_{l}^{t} \quad \forall l,t \tag{41}$$

$$\beta 5_{l,p,c}^{t}+\Psi 5_{l.t}\geq \delta_{C}\hat{\varphi}_{l.t}U_{l,p,c}^{t}cg_{p} \quad \forall l,t,p,c \tag{42}$$

Objective functions

Next, the robust counterpart formulation of the cost objective function is developed. To do so, the objective function (1) can be equivalently transformed as the following constraint:

$$\min z_{costobj}$$
$$Cost\ objective\ function \leq z_{costobj} \tag{43}$$

Then, by introducing the dual vector $\vec{D}_{objcost}$ and dual variable Ψ^{co} , the robust counterpart of constraint (43) is obtained as follows:

$$Cost\ objective\ function+\ \vec{D}_{costobj}+\Gamma^{co}\Psi^{co}\leq z_{costobj} \tag{44}$$

$$\vec{D}_{ocostobj}+\Psi^{co}\geq \vec{U}_{costobj} \tag{45}$$

where vector $\vec{U}_{costof}$ is the uncertain part of the cost objective function, and $\vec{D}_{costobj}$ includes the following terms:

1. revenue from the sale of biodiesel: $\sum_{y}\sum_{b}\sum_{t}\sum_{p}\sum_{l}(pb_{y,b}^{t})(D1_{y,p,l,b}^{t})$;
2. revenue from the sale of glycerin: $\sum_{l}\sum_{g}\sum_{t}(pg_{g}^{t})(D2_{l,g}^{t})$;
3. procurement and transportation cost of CO_2: $\sum_{o}\sum_{l}\sum_{t}(D3_{o,l}^{t})$;

4. procurement and transportation cost of fresh water: $\sum_f \sum_l \sum_t (D4_{f,l}^t)$;

5. procurement and transportation cost of waste water: $\sum_w \sum_l \sum_t (D5_{w,l}^t)$;

6. procurement and transportation cost of brackish water: $\sum_k \sum_l \sum_t (D6_{k,l}^t)$;

7. purchase and transportation cost of nitrogen: $\sum_l \sum_t (D7_l^t)$;

8. purchase and transportation cost of phosphorus: $\sum_l \sum_t (D8_l^t)$;

9. procurement cost of other raw materials: $\sum_r \sum_l \sum_t (D9_{r,l}^t)$;

10. land cost: $\sum_l \sum_p \sum_c \sum_t (D10_{l,p,c}^t)$;

11. biodiesel transportation cost: $\sum_l \sum_b \sum_y \sum_p \sum_t (D11_{y,p,l,b}^t)$;

12. glycerin transportation cost: $\sum_l \sum_g \sum_t (D12_{l,g}^t)$;

13. capital cost of biorefineries: $\sum_l \sum_p \sum_c \sum_t (D13_{l,p,c}^t)$;

14. production cost of biodiesel: $\sum_y \sum_l \sum_p \sum_b \sum_t (D14_{y,p,l,b}^t)$;

15. inventory holding cost of glycerin: $\sum_l \sum_t (D15_l^t)$;

16. inventory holding cost of biodiesel: $\sum_y \sum_l \sum_t (D16_{y,l}^t)$

It should be noted that the uncertain part of the objective function and the dual variables which refer to the uncertain part are written as vector forms which helps keep the notation manageable. Therefore, the robust counterpart of transportation cost of CO_2 in constraint (45), for example, is as follows:

$$D1_{o,l}^{t} + \Psi^{co} \geq to_{O,l} xo_{o,l}^{t} \quad \forall o, l, t \tag{46}$$

In a similar way, the robust counterpart of the GHG objective function can be formulated as follows:

$$\begin{aligned} &\min z_{GHGobj} \\ &GHG\ objective\ function + \vec{D}_{GHGobj} + \Gamma^{go}\Psi^{go} \leq z_{GHGobj} \\ &\vec{D}_{GHGobj} + \Psi^{go} \geq \vec{U}_{GHGof} \end{aligned} \tag{47}$$

where vector $\vec{U}_{GHGof}$ is the uncertain part of the GHG objective function, and $\vec{D}_{GHGobj}$ includes the following terms:

1. GHG emissions of CO_2: $\sum_o \sum_l \sum_t \left(\acute{D}1_{o,l}^{t}\right)$;
2. GHG emissions of fresh water: $\sum_f \sum_l \sum_t \left(\acute{D}2_{f,l}^{t}\right)$;
3. GHG emissions of waste water: $\sum_w \sum_l \sum_t (\acute{D}3_{w,l}^{t})$;
4. GHG emissions of brackish water: $\sum_k \sum_l \sum_t (\acute{D}4_{k,l}^{t})$;
5. GHG emissions of nitrogen: $\sum_n \sum_l \sum_t (\acute{D}5_{n,l}^{t})$;
6. GHG emissions of phosphorus: $\sum_h \sum_l \sum_t (\acute{D}6_{h,l}^{t})$;
7. GHG emissions of other raw materials: $\sum_r \sum_l \sum_t (\acute{D}7_{r,l}^{t})$;
8. GHG emissions of establishing biorefineries: $\sum_l \sum_p \sum_c \sum_t (\acute{D}8_{l,p,c}^{t})$;
9. GHG emissions from open ponds during microalgae growth: $\sum_l \sum_p \sum_c \sum_t (\acute{D}9_{l,p,c}^{t})$;
10. GHG emissions of producing biodiesel: $\sum_y \sum_p \sum_l \sum_b \sum_t (\acute{D}10_{y,p,l,b}^{t})$;

11. GHG emissions of storing biodiesel: $\sum_l \sum_y \sum_t (\acute{D}11^t_{y,l})$;

12. GHG emissions of producing biodiesel: $\sum_y \sum_p \sum_l \sum_b \sum_t (\acute{D}12^t_{y,p,l,b})$;

13. GHG emissions of glycerin transportation: $\sum_l \sum_g \sum_t \left(\acute{D}13^t_{l,g}\right)$;

14. GHG emissions of biodiesel transportation: $\sum_y \sum_l \sum_b \sum_p \sum_t (\acute{D}14^t_{y,p,l,b})$

4. Case Study

To evaluate the performance of the proposed model, a case study was devised to apply the model in an area covering seven Midwestern states of the U.S. These seven states are Indiana, Illinois, Kentucky, Missouri, Nebraska, Iowa, and Kansas. The rest of this section is organized as follows: First, the assumptions made in the case study and the data collection resources and process will be discussed. Then the obtained results will be shown and analyzed.

The assumptions used in the model are described below:

(1) The planning horizon is 7 years which is broken up into 28 three-month periods in order to enable the model to take into account seasonal variations in microalgae growth mentioned in many researches (Lundquist et al., 2010)

(2) The annual amortized capital cost of each biorefinery is estimated by the following annuity formulation (Mohseni et al., 2016):

$$Annulized\ cost = Q \times i/[1-(1+i)^{-n}] \tag{48}$$

where Q is the initial capital cost; i the internal rate of return; and n the project lifetime.

(3) The transportation costs are categorized into three categories of solid commodities trucking, liquid commodities trucking, and transportation by pipeline.

The cost of solid commodities trucking is calculated using the following formulation (Huang, Chen, & Fan, 2010)

$$TC_1 = \sum_l \sum_{I_l} \sum_j [\frac{(t_b^d + \frac{t_b^t}{v}) * d_{I_l j}}{cap_b} + lu_b] * \frac{x_{I_l j}^t}{1 - MC_l} \tag{49}$$

Where t_b^d is the distance dependent cost and t_b^t is the time dependent cost of transportation. cap_b is the capacity of each truck, $d_{I_l j}$ the distance between locations, and lu_b the loading/unloading cost. $x_{I_l j}^t$ is the amount of material being transported and finally MC_l is the moisture content of the material being handled.

The cost of liquid commodities trucking is calculated using the following formulation (Huang et al., 2010):

$$TC_2 = \sum_j \sum_m [\frac{(t_{lq}^d + \frac{t_{lq}^t}{v}) * d_{jm}}{cap_{lq}} + lu_{lq}] * y_{jm}^t \tag{50}$$

Where t_{lq}^d is the distance dependent cost and t_{lq}^t is the rime dependent cost of transportation. cap_{lq} is the capacity of each truck, d_{jm} is the distance between locations, and lu_{lq} is the loading/unloading cost, and y_{jm}^t is the amount of material being transported. The value of all these parameters are adopted from the work by Huang et al. (2010):

Pipeline transportation cost includes the water transportation cost and the CO_2 transportation cost. CO_2 transportation cost has been adapted from the work by Zhang, Wang, Massarotto, & Rudolph (2006); and the water transportation cost from the article by Zhou, & Tol (2005).

(4) Algal biomass productivity is a function of numerous factors such as temperature, light

intensity, oxygen concentration, cultivation culture PH, and nutrient availability which makes it hard to calculate the productivity. To overcome this complexity, algal biomass productivity has been considered a function of temperature and light intensity. This is due to the fact that these two factors have the strongest correlation with the productivity (Béchet, Shilton, Guieysse, 2013). The following formulation has been used to calculate algal biomass productivity which has been tested against experimental results (Jiménez, Cossí, & Niell, 2003).

$$1/P = -0.0802 + (1.676 * 1/T) + (73.491 * 1/I) \tag{51}$$

Where P is productivity (g dry weight/m^2day), T is the temperature of cultivation culture in centigrade and I is the irradiance (kj/m^2day).

In the following paragraphs the data collection resources and process will be discussed.

- CO_2: The number of fossil fuel power plants selected as a source of CO_2 in this study sums up to 26 locations. These power plants have been selected based on their CO_2 emission capacity and location. The seven states in which the case study is carried out have been divided to counties and the suitable locations have been selected based on the average temperature and sunshine hours obtained from U.S Climate Data (2017). The total amount of CO_2 available by the selected 26 power plants is approximately 250 million metric tons per year.
- Fresh water: The 23 fresh water sources used in the case study have been selected using the Water Resources of the United States National Water Information System (NWIS)

Mapper (2017). The suitability of locations has been determined using the same method employed for CO_2 power plant locations.

- Waste water: The information of waste water sources has been retrieved from different county and state websites in which the waste water treatment plants are located. In total, 16 waste water treatment plants have been selected to provide waste water to production facilities.
- Brackish water: Brackish water sources of the supply chain network are Mississippi McNairy-Nacatoch aquifer of River Valley alluvial aquifer and Mississippian aquifer. The location, capacity, depth of water, and other necessary information related to these aquifers has been obtained from an article by Osborn, Smith, and Seger (2013).
- Nitrogen: In order to provide the nitrogen required for algae cultivation, ammonia production facilities have been selected with respect to their capacity and location. The total amount of nitrogen available by purchase of fertilizer is 6.719 million tons per year.
- Phosphorus: Selection of phosphorus fertilizers sources was a challenge in this case study as production facilities providing phosphorus fertilizers are not as prevalent as that of other resources. However, due to the fact that the phosphorus requirement of algae is less than other necessary resource, production facilities have been selected without rigorous restrictions on the location.
- Other raw materials: The other required raw materials will be procured from the local markets as the amounts consumed are relatively low.

- Biorefinery locations: The candidate locations for biorefinery foundation have been selected using Land Cover Data Viewer map of National Gap Analysis Program administrated by United States Geological Survey (2017). The priority of selection has been given to shrub lands and grasslands, nonvascular and sparse vascular rock vegetation, and recently disturbed land cover categories.
- Demand zones: The demand zones to which the produced biofuels and co-products will be distributed, have been considered the biggest cities of the seven states included in the case study.

5. Results and Analysis

This section presents and analyzes the results of both deterministic and robust proposed models including optimal objective functions (total supply chain cost and GHG emission), optimal supply chain design (facility location, production pathway and capacity) as well as sensitivity analysis evaluating the effect of different input parameters on the optimal results. The model was coded in GAMS software and solved by the commercial solver CPLEX on a personal computer equipped with CPU 3.16 GHz and 4G RAM. The multi objective solution approach utilized to obtain the results is the augmented ε-constraint method (Mavrotas, 2009).

5.1 Deterministic Supply chain cost and GHG emission

To solve the problem, the model is solved with one objective first. Afterwards, the model is solved with the other objective function while the first objective function is turned into a constraint with its optimal value as the right hand side of the constraint. Then the range obtained by these optimal and nadir values, is divided into five equal sections by six grid points which are used as the values of ε to generate six Pareto-optimal solutions. Table 3 includes the optimal values of the total cost and GHG emission objective functions.

As might be expected, it is clear that two objective functions are in conflict with each other, meaning that as GHG emission value is reduced, total cost rises and vice versa.

Table 3: Computational results under different satisfaction degrees of objective functions.

Solution	Objective function value		CPU time (sec)
	Of_{cost}	Of_{GHG}	
A	9.448E+09	7.291E+09	1145
B	1.09E+10	6.871E+09	3451
C	1.234E+10	6.745E+09	3251
D	1.379E+10	6.694E+09	2589
E	1.524E+10	6.656E+09	3210
F	1.668E+10	6.608E+09	1945

According to this, obtaining a more environmentally friendly biodiesel leads to increased supply chain cost. However, it is of great importance to find an acceptable trade-off between cost and GHG emission which satisfies decision maker criteria. To this aim, it should be considered how much supply chain cost would increase by reducing different amounts of GHG emission. For example, when GHG emission decreases from 7.3E+09 to 6.6E+09 (kg CO_2-eq), supply chain cost grows significantly to a peak of $1.66E+10 which is about two times the cost of the supply chain emitting 7.3E+09 (kg CO_2-eq) GHG, but the cost rises only marginally from $9.44E+09 to $1.09E+10 by reducing GHG emission from 7.3E+09 to 6.9E+09 (kg CO_2-eq). In other words, as reduction in GHG emission increases, the cost of environmental protection grows exponentially. This trend is clearly seen in the Pareto optimal frontier shown in Figure 8.

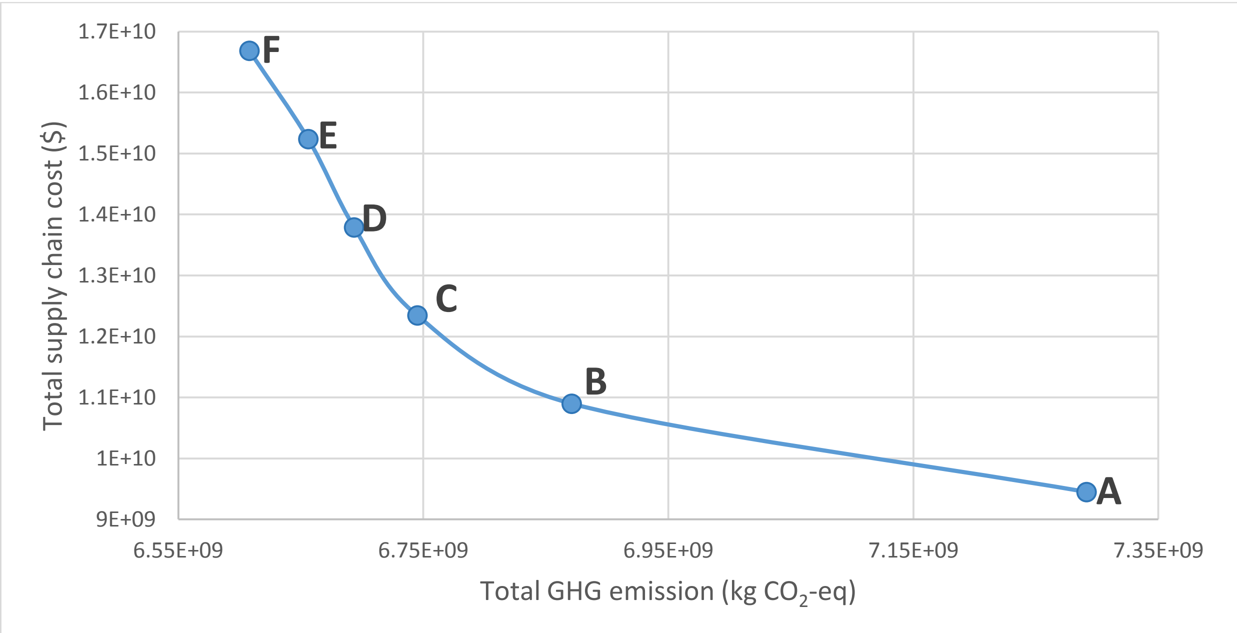


Figure 8: Trade-off between economic and environmental objective functions

Therefore, GHG emission of microalgae biodiesel supply chain can become close to the most environmental optimum solution with a small increase in production cost, which shows an obvious advantage in considering economic and environmental objective functions in microalgae biodiesel supply chain simultaneously. The last column of Table 3 shows that the computational time of all model iterations is under one hour which is satisfactory as the proposed model is aimed at optimizing strategic supply chain decisions.

5.2 Deterministic Supply chain design

Figure 9 shows the optimal facility locations, production pathways and capacities between 2018 and 2024 for two efficient solutions B and E chosen from Table 3. In solution B, five biorefineries with production pathway 14 will be built in 2018. This will increase to ten biorefineries with production pathway 14 and two with production pathway 16 three years later and then to fourteen biorefineries with production pathway 14, five with production pathway 16 and two with production pathway 12 in 2024. On the other hand, solution E suggests that five and thirteen biorefineries with production pathway 12 should be founded by the year 2018 and 2021 respectively. As the demand of biodiesel continues to rise, six biorefineries with production. pathway 12 and two with production pathway 14 will be additionally needed in 2024 can be justified by the fact that solution B focuses on the reduction of supply chain cost more than GHG emission. It determines the most economic pathways with lower GHG emission such as pathways 14 and 16 while solution E selects more environmental pathways such as pathway 12 to achieve lower GHG emission than solution B. The results also indicate that two optimal designs select different locations for biorefineries. In 2018, for example, locations 5, 6, 7, 8 and 10 are optimal locations in solution B compared to locations 6, 8, 9, 12 and 21 in solution E. Consequently, the location and the type of pathway are highly influenced by changing the preferences in the objective functions.

Another important aspect illustrated by Figure 6 is the clear importance of economy of scale. In other words, both designs almost prescribe maximum capacity level for biorefineries which

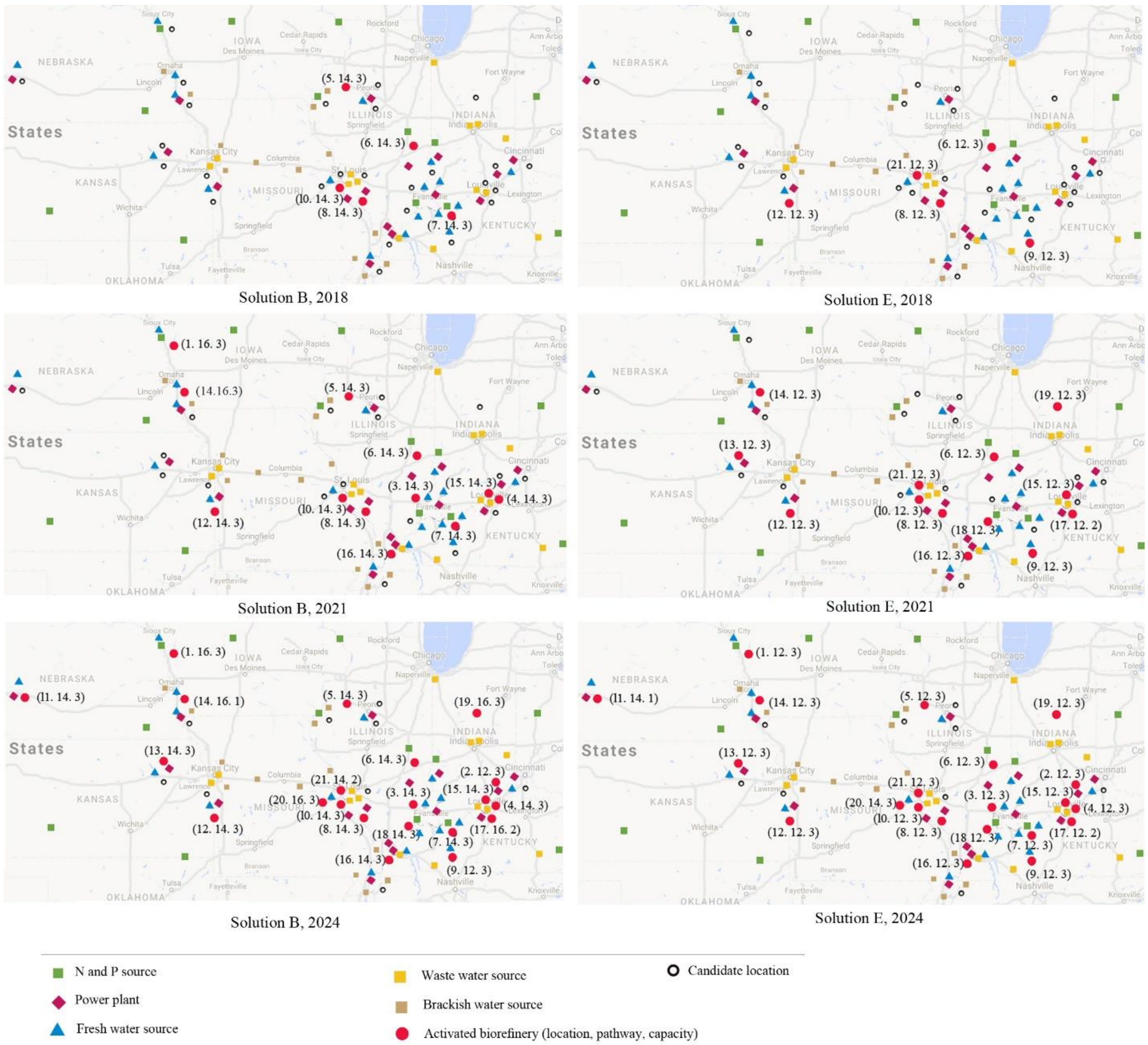


Figure 9: Optimal supply chain design for solutions B and E between 2018 and 2024
This difference seen between the types of optimal production pathways chosen by each design

leads to fewer biorefineries with higher capacities, that is to say a centralized supply chain structure. Therefore, economy of scale is of benefit to the proposed model, while in some biomass supply chains, lower cost of larger biorefineries might be counteracted by the increased cost of transporting heavy raw materials for longer distance (Yue et al., 2014). The numbers mentioned in Figure 6 follow the format of (Location, Production pathway, Capacity). Three capacities have been considered for each biorefinery which are 400, 1000, and 2000 (ha) cultivation ponds.

5.3 Deterministic Sensitivity analysis

As emphasized by many researchers, there are a number of factors that play a significant role in determining the production cost of microalgal biodiesel, including: (1) growth rate, (2) conversion rate, (3) CO_2 demand, (4) land cost, (5) water transportation cost and (6) CO_2 transportation cost (Lundquist, 2010; Davis, Aden, & Pienkos, 2011). To evaluate the effect of these factors, a sensitivity analysis is performed in this section which helps analyze how the total cost can be reduced to a competitive cost in comparison to traditional fossil fuels. The value of factors considered in the analysis are changed according to ranges shown in Table 4.

The results illustrated in Figure 10 reveal that growth rate and lipid content have the greatest effect on the unit production cost. A positive change of 20% in these parameters, respectively, leads to reductions of around 14% and 19% in the optimal production cost, and a negative change of 20% in these parameters, respectively, increase the cost by over 10% and 15%.

Table 4: Sensitivity analysis parameters.

Scenario No	Sensitivity parameter	Variation range (%)
0	Base model	
1^+	Growth rate	+20
1^-	Growth rate	-20
2^+	Conversion rate	+20
2^-	Conversion rate	-20
3^+	CO_2 demand	+20
3^-	CO_2 demand	-20
4^+	Land cost	+20
4^-	Land cost	-20
5^+	Demand	+20
5^-	Demand	-20
6^+	water transportation cost	+20
6^-	water transportation cost	-20
7^+	CO_2 transportation cost	+20
7^-	CO_2 transportation cost	-20

Based on this finding, more focus should be put on increasing microalgae lipid content than growth rate as there is a traditional trade-off between improvements in these two parameters (Davis et al., 2011). Land cost constituting a high proportion of the unit cost is the next important parameter which can be considered as one of the significant cost reduction potentials. For example, a 20% reduction in land cost causes a change of approximately 10% in the unit cost. Accordingly, the government can help make microalgae biodiesel cost-competitive by offering.

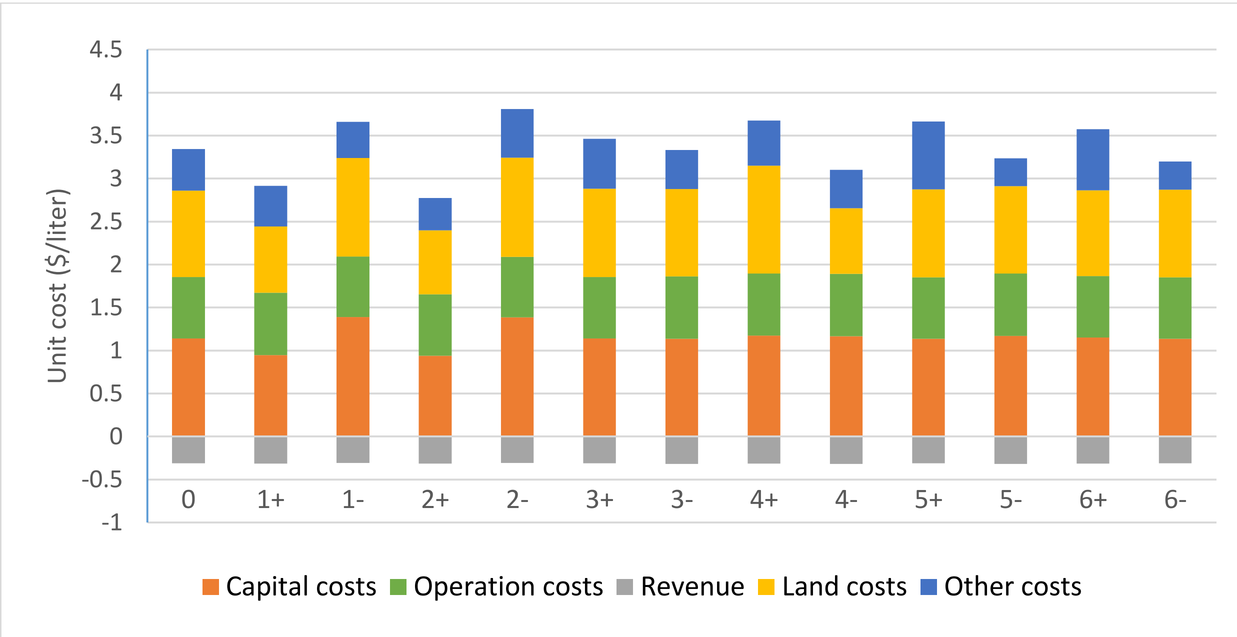


Figure 10: Results of the sensitivity analysis.

low-cost land for microalgae production. Among the other parameters evaluated, the effect of change in water and CO_2 transportation cost is noticeable as they reduce the unit cost by around 4% and 5% respectively. This suggests that future waste water treatment stations and power plants should be constructed near locations with high average temperature and solar irradiance which is suitable for microalgae production. Finally, the unit cost is less sensitive to change in nitrogen and phosphor requirements which indicates the proposed model does not depend on use of expensive fertilizers heavily because nitrogen and phosphor requirements can be met by waste water nutrients and residues after anaerobic digestion as a source of nutrients.

As stated previously, one of the advantages of this article's model is satisfying the water requirements through various water sources (*i.e.*, fresh, brackish, and waste water) to address the concern of high water consumption of microalgae production which raises the issue of sustainability. To evaluate the impact of using various water sources instead of only fresh water on the unit cost, one of these sources is considered in each iteration and the model is forced to use it by replacing the availability parameters of the other two sources with zero, then the amount of water requirement (mw) is changed by ± 20 and the model is run again. The result of this experiment along with basic model which can use all sources without restriction are shown in Figure 11. At first sight, it can be clearly seen that sole use of fresh and brackish water increase the unit cost much more than individual use of waste water. This is because waste water not only provides the water required to grow microalgae, but it also reduces the need of fertilizer which accounts for a high proportion of production cost. Another point is that the effect of sole use of fresh water on the unit cost is bigger than that of brackish water which is due to the higher price of fresh water than brackish water. The results also indicate that the difference between unit costs becomes larger with increase in water requirement factor. This highlights the importance of using various water sources in regions where microalgae need more water for growth. Therefore, besides the fact that the combined use of fresh, brackish and waste water reduces the barriers of large scale production due to the limited fresh water resources, it can be considered as one of important cost reduction potentials.

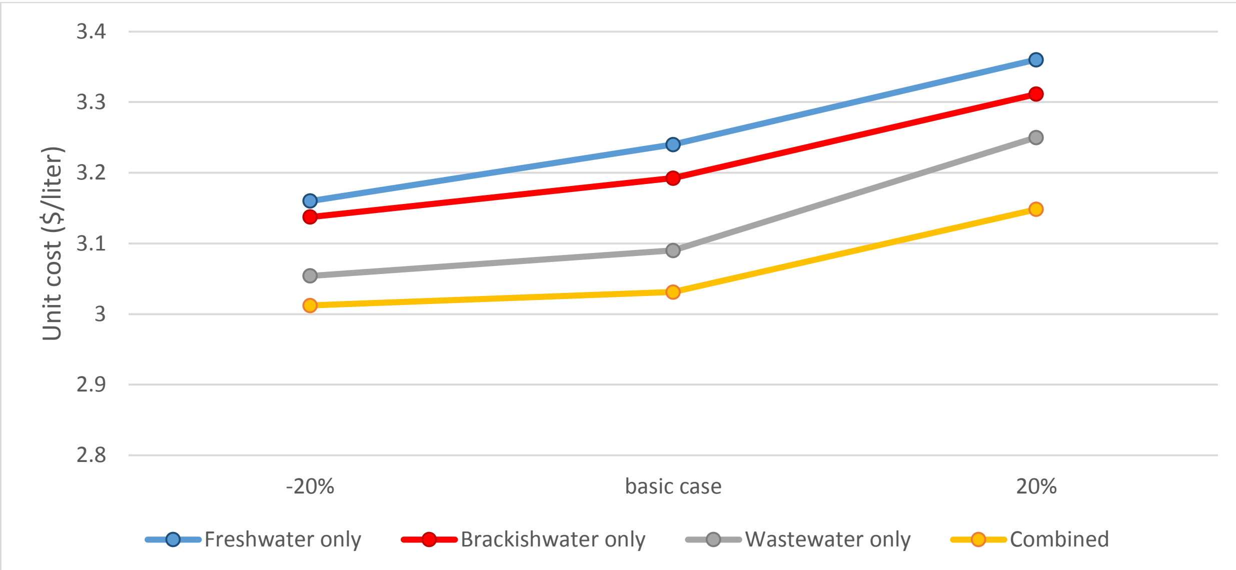


Figure 11: Impact of individual use of different water sources on unit cost.

The rest of this section is organized as follows:

The results of the robust model are represented and the differences between the robust and deterministic models are illustrated by comparing the optimal objective function values and supply chain designs of the robust model with those of the deterministic model. For robust solutions, various conservatism levels (95%, 80% and 65%) are considered in order to evaluate how the alternation of risk preference affects supply chain solutions. This flexibility offers supply chain decisions which have different reliability degrees enabling the decision maker to make a realistic trade-off between the robustness of solutions and their cost which is the increase in total supply chain cost and GHG emission. Amplitude of uncertain parameters which is an important factor during robust optimization process is set to 10%, 20% and 30% in each iteration. The advantage of considering different perturbation levels is that the decision maker can find their preferred solution which is ensured to remain optimal even if uncertain parameters vary within the amplitude range. Clearly, increase in robustness of solution raises the total cost and GHG emission which should be balanced according to the risk preference of the decision maker.

5.4 Robust Supply chain cost and GHG emission

In order to have similar conditions for the robust and deterministic models, six grid are used as the values of ε. Table 5 shows the optimal values of the total cost and GHG emission objective functions for all possible combinations of conservatism levels and amplitude ranges. This result is also graphically represented in Figure 12.

As can be seen, the value of both objective functions grows when higher reliably levels are used. For example, allowing for 10% parturition, robust model with 95% reliability level has the total cost of 1.71E+10 and GHG emission of 1.31E+10, which are significantly greater than the corresponding figures of (1.14E+10, 8.90E+09) in the robust model with 65% reliability level. This means that the decision maker has to pay more cost for solutions which remain optimal for more possible values of uncertain parameters in the amplitude range. The maximum level of reliability ensures robust solutions for all possible values of uncertain parameters but on the condition that they vary only in the considered amplitude range. Therefore, it is of great importance to evaluate the effect of remaining optimal for wider ranges of uncertain parameters on the total cost and GHG emission.

Table 5: Computational results under different reliability levels and perturbation levels.

	perturbation	Objective function value								
		Reliability level=65%			Reliability level=80%			Reliability level=95%		
		Of_{cost}	Of_{GHG}	Time (s)	Of_{cost}	Of_{GHG}	Time (s)	Of_{cost}	Of_{GHG}	Time (s)
A	10%	1.14E+10	8.90E+09	2514	1.44E+10	1.10E+10	2741	1.71E+10	1.31E+10	1012
B	10%	1.32E+10	8.38E+09	2895	1.65E+10	1.07E+10	2548	1.97E+10	1.26E+10	3254
C	10%	1.50E+10	8.16E+09	2465	1.86E+10	1.05E+10	2654	2.23E+10	1.25E+10	3287
D	10%	1.68E+10	8.10E+09	2145	2.08E+10	1.04E+10	2754	2.50E+10	1.22E+10	2590
E	10%	1.86E+10	8.05E+09	1245	2.29E+10	1.02E+10	2451	2.76E+10	1.20E+10	3251
F	10%	2.03E+10	8.03E+09	1814	2.50E+10	9.91E+09	2651	3.02E+10	1.19E+10	1946
A	20%	1.41E+10	1.07E+10	1218	1.63E+10	1.27E+10	2415	1.98E+10	1.57E+10	1547
B	20%	1.62E+10	9.96E+09	1718	1.88E+10	1.24E+10	3211	2.29E+10	1.53E+10	1685
C	20%	1.83E+10	9.85E+09	2528	2.12E+10	1.19E+10	2217	2.60E+10	1.50E+10	1354
D	20%	2.04E+10	9.77E+09	2925	2.37E+10	1.17E+10	2514	2.92E+10	1.49E+10	2415
E	20%	2.26E+10	9.75E+09	4512	2.61E+10	1.16E+10	2321	3.23E+10	1.46E+10	2658
F	20%	2.47E+10	9.71E+09	1416	2.85E+10	1.15E+10	2145	3.54E+10	1.39E+10	2928
A	30%	1.68E+10	1.30E+10	1323	1.80E+10	1.39E+10	3231	2.32E+10	1.82E+10	2698
B	30%	1.93E+10	1.22E+10	1423	2.08E+10	1.33E+10	3110	2.69E+10	1.72E+10	2784
C	30%	2.18E+10	1.19E+10	1024	2.36E+10	1.31E+10	2728	3.05E+10	1.70E+10	2958
D	30%	2.43E+10	1.17E+10	2541	2.63E+10	1.29E+10	2152	3.41E+10	1.69E+10	2010
E	30%	2.68E+10	1.16E+10	3230	2.91E+10	1.27E+10	3635	3.77E+10	1.67E+10	1578
F	30%	2.94E+10	1.14E+10	3215	3.19E+10	1.26E+10	3207	4.14E+10	1.65E+10	1025

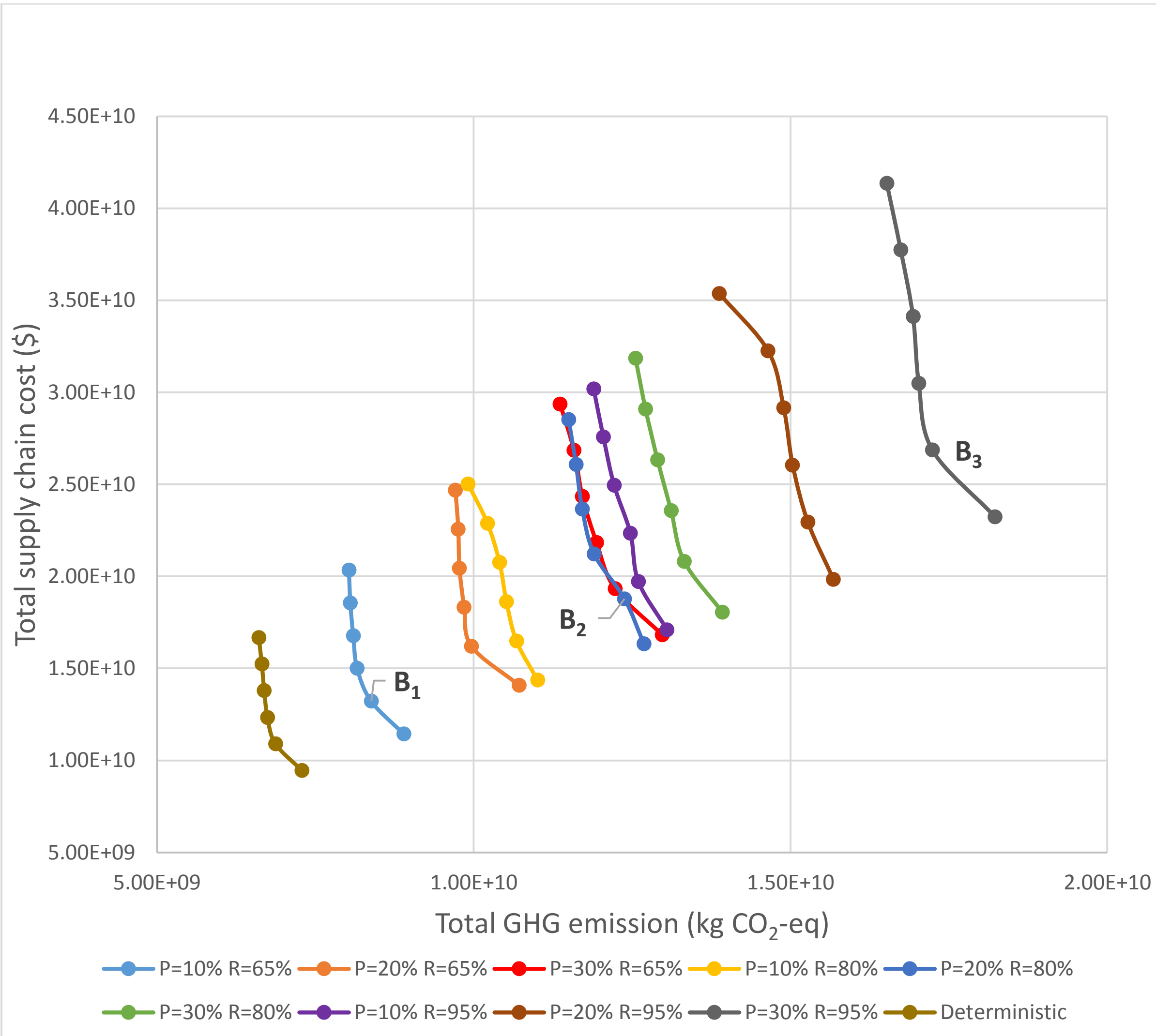


Figure 12: Economic and environmental objective functions with different reliability levels and amplitude ranges.

From the results, under the reliability level of 65%, total cost and GHG emission increase from (1.14E+10, 8.90E+09) for 10% amplitude to (1.68E+10, 1.30E+10) for 30% amplitude. In other words, (0.54 E+10, 0.41E+10) is the additional cost that should be paid to keep the robustness of solutions when the amplitude range increases from 10% to 30%. The above results indicate that wider amplitude ranges and higher reliability levels which provide solutions with a higher confidence level impose additional costs, but there is no specific rule to select the best solution. Because the preference of decision maker is the main criterion that determines the required confidence level and subsequently the best robust solution. Finally, Table 5 shows that robust optimization approach does not have a negative effect on computational time although it needs more variables and parameters which increase the problem size.

5.5 Robust supply chain design

Figure 13 manifests the optimal supply chain design for efficient solutions B_1, B_2 and B_3 from Figure 12 which are determined by considering three combination of reliability levels (R) and perturbation ranges (P): (R=65%, P=10%), (R=80%, P=20%) and (R=95%, P=30%) that represent optimistic, realistic and pessimistic viewpoints of the decision maker. Comparing this supply chain design with that obtained by the deterministic model shows that the robust model determines more biorefineries than the determinist model does. In 2024, for example, the robust model with (R=65%, P=10%) opens 22 biorefineries compared to 21 biorefineries in the determinist design. This difference becomes greater as the reliability level and perturbation range increase until it reaches 4 biorefineries for R=95% and P=30%. This result can be explained by

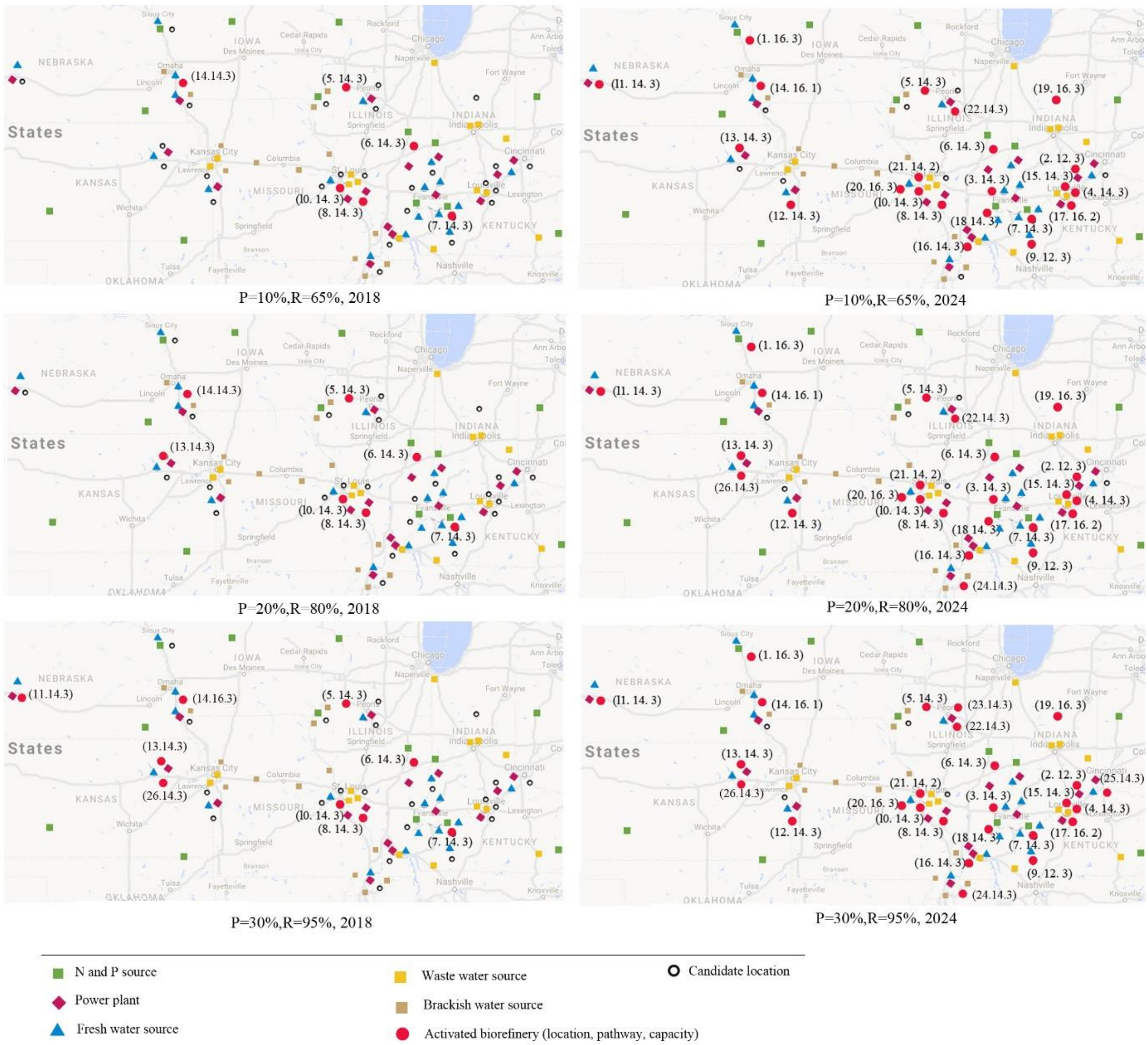


Figure 13: Robust supply chain design for solutions B1, B2 and B3 in 2018 and 2024.

the fact that the robust model needs more biorefineries to satisfy the demand even when microalgae production decreases due to lower growth rate. Another point is that although the number of biorefineries is different in the robust and deterministic model, but their optimal locations is the same. There is also no difference in the capacity and production pathway of biorefineries between the robust and deterministic model. This means that these supply chain decisions remain optimal in the presence of data perturbation and can be used as stable decisions for decision making while the number of the required biorefineries loses its optimality with small data perturbation. Therefore, a reasonable decision maker should not rely on the number of biorefineries determined by the deterministic model.

6. Conclusion

The present study develops a comprehensive algal biofuel supply chain multi objective model for a sustainable biodiesel production. The model demonstrates that environmental factors (*i.e.* GHG emission) can be considered without compromising the main objective of cost competitiveness drastically. As illustrated, a 420,000 ton reduction in GHG emission can be achieved with only 15% increase in the total supply chain cost which is quite impressive considering the new challenges the world is facing such as global warming. This also addresses plans, such as RFS, established by EISA which mandate at least 50% reduction in GHG emission in production of biofuels in comparison to that of their petroleum counterparts. This study also provides guidelines for future research endeavors such as focusing on lipid content improvement which would offer more economic benefits than focusing on productivity improvement as typically there is a tradeoff between these two improvements in reality. Moreover, the benefits of using multiple water resources in the algal biofuel supply chain networks were shown and it can be concluded that the use waste water can reduce the sensitivity of the unit cost to the availability and cost of fertilizers that are of great importance in the supply chains not utilizing waste water. The robust model results indicate that the number of biorefineries founded are quite sensitive to the perturbation of uncertain parameters while the location and capacity of biorefineries are not influenced by the perturbations. In addition, the robust model determines the associated cost of the reliability degree desired by the decision maker and although it incurs additional costs in terms of supply chain total cost and GHG emission, these costs are quite logical to pay as the probability of each realization of the parameters considered in the deterministic model tends to zero. As for future improvements, a thorough GIS analysis for candidate facility locations and resources would help the applicability and reliability of the solutions offered. It was observed that the locations play a major role in the optimality of different scenarios which highlights the benefits of utilizing more precise locating tools like GIS.

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