International Conference on Applied Energy 2019
Aug 12-15, 2019, Västerås, Sweden
Paper ID: 805

OPTIMIZING THE MACROALGAE-BASED BIOFUEL SUPPLY CHAIN UNDER MULTIPLE UNCERTAINTIES – KOREAN CASE STUDY

Mohammad Amin Zarei, Jay Liu*

Pukyong National University, Department of Chemical Engineering, Busan, Nam-gu, Yongso-ro, 45, Republic of Korea
jayliu@pknu.ac.kr

ABSTRACT

The growing global population and the resulting excess use of fossil fuels have brought the urgency for climate change mitigation leading to focus on renewable energy resources. Biomass is one of the earliest natural sources of energy, which has the potential to substitute for primary energy resource. However, commercial production of biofuel is still constrained by uncertainties such as biofuel demand. In this study, a two-stage stochastic mixed integer linear programing is formulated for biofuel supply chain based on macroalgae resource under uncertainties. The objective function in this formulation is total annual cost to be minimized. The approach is illustrated through a bioethanol supply chain case study in Korea, where macroalgae are among the dominant biomass resources.

Keywords: biofuel supply chain, uncertainty, two stage stochastic programing, sustainability, macroalgae

1. INTRODUCTION

Concerns about climate change, energy security, and the diminishing supply of fossil fuels have encouraged the development of biofuel industry[1]. First generation biofuel from food crops and second generation biofuels from lignocellulosic biomass have largely accounted for the most of the biofuel production [2].

However, the production of biofuels from these sources has led to a series of problems, such as rising food prices and competition for agricultural land[1]. These problems have raised interest in developing biofuel from non-edible biomass resources. Using macroalgae can be considered an alternative to these issues since: 1) macroalgae grow in marine systems and also very efficient in utilizing the nutrients from waste water; 2) they mainly consist of carbohydrates, which are good candidates for biofuel production like ethanol[3].
In the biofuel supply chain (BSC), biomass is transported from supply through facilities where it undergoes various processes including cultivation, harvesting, storage, conversion to biofuel, and distribution to demand zones. Efficiency of this chain is essential for biofuel development projects. Indeed, as the biomass itself is relatively cheap, the economic equilibrium of the whole system critically depends on logistic costs[4,5]. Therefore, the main objective in designing the BSC is to optimize the total cost for managing of the supply chain.

Another main challenge comes from uncertainties inherent in biomass supply, demand, production, transportation, operation, and prices of BSC[6]. There are several review papers focused on uncertainties in these chains[7]. Based on those investigation biomass supply and biofuel demand parameters are the most important uncertain parameters in BSC that are considered in this work. In this paper, we developed two stage stochastic mixed integer linear programming for macroalgae-based biofuel supply chain management (MBBSCM). To the best of our knowledge, this study is the first study applying biomass supply and demand for MBBSCM.

2. MACROALGAE-BASED BIOETHANOL SUPPLY CHAIN MANAGEMENT(MBBSCM)

This paper deals with the strategic design and planning of stochastic MBBSCM in multiple periods. As shown in Fig 1 the structure includes nodes referring to processes such as harvesting sites, dryers, refinery, biomass storage, and biofuel storage. Also, trucks, trains, ships, or planes can transport biomass or biofuel between nodes shown by arrows.

Selection and peer-review under responsibility of the scientific committee of the 11th Int. Conf. on Applied Energy (ICAE2019).
Copyright © 2019 ICAE

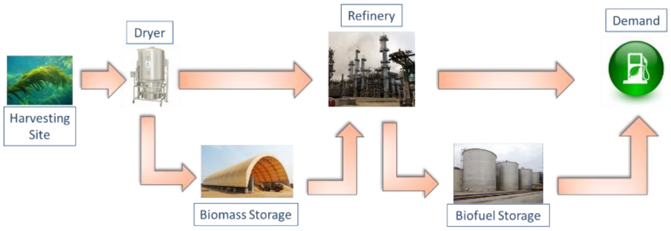


Fig 1 Underlying structure of the biofuel supply chain network.

First, the deterministic model will be described briefly and then focus on stochastic equations to consider uncertainties. At harvesting sites, available amount of biomass is given for each site and each time period and the amount of harvesting is considered as a decision variable. It should be also noted that fresh macroalgae harvested have considerable amount of water (85 wt. %). Therefore, biomass should be dried for more efficient transportation and storage[8]. Hence, biomass feedstock is shipped from a harvesting site to a dryer directly. The location of dryer can be optimized by the optimization model. To increase the operational flexibility of MBBSCM, there is no constraint set to affect the potential location of a dryer. To propose a flexible model for MBBSCM, there is possibility to use dryers with different technologies and capacities with respect to the amount of feedstock. The extra macroalgae dried and bioethanol produced are stored in biomass and biofuel storage, respectively.

The costs of biomass conversion are given for each potential biorefinery at various capacity levels. The process models of biorefinery is very complicated; however, to simplify the MBBSCM model and decrease calculation load, we have modified biorefinery models developed in [9]. Finally, the biofuel demand in each time period for each demand zone is given.

3. MBBSCM MODELLING

A mixed integer linear programing (MILP) is developed incorporating biomass supply and biofuel demand uncertainties.

In problems of stochastic optimization of supply chain, the planning decisions is strategic and thus made before dealing with uncertainties in first stage. On the other hand, since operational decisions are more flexible, they are made in the second stage[10]. In our work, location of technologies (integer variable) and capacity expansion of them are first-stage decision variables. The second stage covers all operational decision variable (continues variable) including: amount of biomass and biofuel for transportation, biomass supply and biofuel production.

It is known that this uncertain data in this model cannot be solved with continuous distribution. Thus, discrete distribution should be used for uncertain random parameters[11]. Both the uncertanitiy of biomass supply and biofuel demand are represented by three possible value: low, medium with equal probability. Then the model can be expressed as:

$$Min\ (Cost) = Cost_{1st} + prb_s \times Cost_{2nd}$$
$$Cost_{1st} = C^{fx} + C^{D} + C^{MS} + C^{FS}$$
$$Cost_{2nd} = C^{OM} + C^{BTRS} + C^{ETRS} + C^{IM}$$

where scenario-based $Cost$ is total annual cost with the probity prb_s associated with each random feedstock yield scenario s calculated by two stages: $Cost_{1st}$ and $Cost_{2nd}$. The location of technologies and their capacity are considered in first stage where capital costs of biorefinery (C^{fx}), dryer (C^{D}), biomass storage (C^{MS}), and biofuel storage (C^{FS}) are included in $Cost_{1st}$. The second stage covers all operational decision variables (continuous variables) where C^{OM}, C^{BTRS}, C^{ETRS} and C^{IM} represent operation and maintenance cost of biorefinery, cost of biomass transport, biofuel transport and import, respectively.

Sources of uncertainties in biofuel supply chain have been investigated in several works where they were classified by type of uncertanitiy[6,12]. In order to find the probability of each scenario, one can focus on source of uncertainties[13] or assume random probability[10]. In this work, we assume random and equal value for both biofuel demand and biomass supply.

4. CASE STUDY

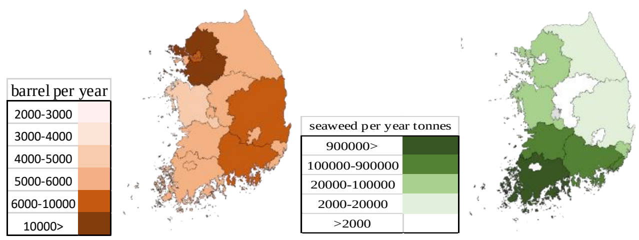
The performance of the proposed stochastic models is demonstrated through a case study developed for a conceptual biofuel supply chain in South Korea. The 99.6% of seaweed aquacultured produced by quantity in south east Asia[14]. *Saccharina japonica* that one of the main seaweed crops[15] is considered in this study as biomass feedstock.

Table 1 Probability of scenarios.

Scenario	prb_s	*Biomass supply coef.*	*Biofuel demand coef.*
S1	0.1	0.9	0.9
S2	0.1	0.9	1
S3	0.1	0.9	1.1
S4	0.1	1	0.9
S5	0.1	1	1
S6	0.1	1	1.1
S7	0.1	1.1	0.9
S8	0.1	1.1	1
S9	0.1	1.1	1.1

Copyright © 2019 ICAE

Korea consists 15 provinces/districts (excluding Jeju), which has specific amount of biomass supply and biofuel demand. Total 9 scenarios (Table 1) are developed in this work to account uncertainties in the biofuel supply chain in Korea. In each scenario demand and supply are changed by ±10 %. All provinces/districts are considered a potential location of facilities. The time horizon is decomposed into a finite number of time periods. I.e., the time horizon is one year, and the time period is fixed to one month to be coherent with the data. In this study we consider 5% of current gasoline usage replaced by ethanol (E5). The available amount of biomass and biofuel demand are shown in Fig 2.



(a)biofuel demand *(b) resource of biomass*

Fig 2 distribution of biomass resources and biofuel demand.

The biorefinery technology considered in this work is based on the superstructure developed in [16] with capacity ranges of 0–7.5 million gallons per year (MGY), 7.5–15.5 MGY, 15.5-23 MGY, 23–31 MGY and 31– 38 MGY. The dryer used is bed drying, which decrease the moisture of wet biomass from 85% to 15 %[1].

5. RESULTS

The proposed model with 180 binary variables, 29,700 integer variables, and 58,239 continuous variables was coded in in GAMS software and solved by DE solver on a 3.00 GHz processor.

In this work all scenario has same probability and the expected cost of province-level supply chain is $488,265,700. We called S3 as worst scenario since the biomass supply is lowest and biofuel demand is the highest rate. Also, the highest coefficient of biomass supply and the lowest biofuel demand belong to S7 called best scenario.

The amount of biofuel demand based on E5 can be met in the worst scenario is 73 percent and the rest of demand should be imported from overseas. For the best scenario 10 % of biofuel produced is extra and can be exported.

Table 2 Number of facilities needed for each scenario.

	7.5 MGY	***15.5 MGY***	***23 MGY***	***31 MGY***	***38 MGY***
S1	9	0	0	0	6
S2	9	0	0	0	6
S3	9	0	0	0	6
S4	8	0	0	0	7
S5	8	0	0	0	7
S6	8	0	0	0	7
S7	8	0	0	0	7
S8	7	0	0	0	8
S9	7	0	0	0	8

(a) Refinery

	325 *DTPY**	***2,602*** *DTPY*	***20,817*** *DTPY*	*1,332,308 DTPY*
S1	1	3	4	1
S2	2	4	3	1
S3	1	3	4	1
S4	2	4	3	1
S5	1	3	5	1
S6	2	4	3	1
S7	2	3	4	1
S8	2	3	4	1
S9	2	2	5	1

(b) Dryer

* dry tons per year

The cost of biofuel supply chain highly depends on building biorefinery with fixed capacity and transporting biomass and biofuel. Therefore, choosing the best location for facilities is the main goal of this paper. Table 2 shows the number facilities needed in each scenario. As shown in Table 2(a) all scenarios, biorefineries is built in all providences/districts. However, since macroalgae can be harvested in coastal region, they have the higher capacity refinery.

6. CONCLUSION

Considering uncertainties in biofuel supply chain is vital to the development of biofuel industry. In this study, we have developed an optimization approach for MBBSCM in Korea. A two-stage mixed-integer linear programing (MILP) problem considering uncertainties in biomass supply and biofuel demand was developed in order to consider the main characteristics of biofuel supply chains. The MILP model concurrently predicts the optimal network design, facility location, capital investment and inventory control. To the best of our knowledge, this study is the first study applying two main

Copyright © 2019 ICAE

uncertainty characteristics of macroalgae-based biofuel supply chain. The proposed model can be applied to large-scale biofuel production under biomass supply and biofuel demand.

Focusing the source of uncertainties sources and their effect on the model could be a possible extension of this work. Moreover, the two-stage stochastic programming method lacks the capability of the sequential decision-making process based on evolving uncertainties over time, multistage stochastic programing highly recommended for extension of this work.

ACKNOWLEDGEMENT

This research was supported through the Basic Science Research Program of the National Research Foundation of Korea (NRF) funded by the Ministry of Science and ICT (2017R1A2B4004500).

REFERENCE

[1] Mohseni S, Pishvaee MS. A robust programming approach towards design and optimization of microalgae-based biofuel supply chain. Comput Ind Eng 2016;100:58–71. doi:https://doi.org/10.1016/j.cie.2016.08.003.

[2] Zandi Atashbar N, Labadie N, Prins C. Modelling and optimisation of biomass supply chains: a review. Int J Prod Res 2018;56:3482–506.

[3] Jiang R, Ingle KN, Golberg A. Macroalgae (seaweed) for liquid transportation biofuel production: what is next? Algal Res 2016;14:48–57. doi:https://doi.org/10.1016/j.algal.2016.01.001.

[4] Ba BH, Prins C, Prodhon C. Models for optimization and performance evaluation of biomass supply chains: An Operations Research perspective. Renew Energy 2016;87:977–89. doi:https://doi.org/10.1016/j.renene.2015.07.045.

[5] Atashbar NZ, Labadie N, Prins C. Modeling and optimization of biomass supply chains: A review and a critical look. IFAC-PapersOnLine 2016;49:604–15. doi:https://doi.org/10.1016/j.ifacol.2016.07.742.

[6] Bairamzadeh S, Saidi-Mehrabad M, Pishvaee MS. Modelling different types of uncertainty in biofuel supply network design and planning: A robust optimization approach. Renew Energy 2018;116:500–17. doi:https://doi.org/10.1016/j.renene.2017.09.020.

[7] Ghaderi H, Pishvaee MS, Moini A. Biomass supply chain network design: An optimization-oriented review and analysis. Ind Crops Prod 2016;94:972–1000. doi:https://doi.org/10.1016/j.indcrop.2016.09.027.

[8] Gallagher JA, Turner LB, Adams JMM, Dyer PW, Theodorou MK. Dewatering treatments to increase dry matter content of the brown seaweed, kelp (Laminaria digitata ((Hudson) JV Lamouroux)). Bioresour Technol 2017;224:662–9.

[9] You F, Tao L, Graziano DJ, Snyder SW. Optimal design of sustainable cellulosic biofuel supply chains: Multiobjective optimization coupled with life cycle assessment and input–output analysis. AIChE J 2011;58:1157–80. doi:10.1002/aic.12637.

[10] Xie F, Huang Y. A multistage stochastic programming model for a multi-period strategic expansion of biofuel supply chain under evolving uncertainties. Transp Res Part E Logist Transp Rev 2018;111:130–48. doi:https://doi.org/10.1016/j.tre.2018.01.015.

[11] Senna P, Pinha D, Ahluwalia R, Guimarães JC, Severo E, Reis A. A three-stage stochastic optimization model for the Brazilian biodiesel supply chain. Production 2016;26:501–15.

[12] Awudu I, Zhang J. Uncertainties and sustainability concepts in biofuel supply chain management: A review. Renew Sustain Energy Rev 2012;16:1359–68. doi:https://doi.org/10.1016/j.rser.2011.10.016.

[13] Quddus MA, Chowdhury S, Marufuzzaman M, Yu F, Bian L. A two-stage chance-constrained stochastic programming model for a bio-fuel supply chain network. Int J Prod Econ 2018;195:27–44. doi:https://doi.org/10.1016/j.ijpe.2017.09.019.

[14] Nayar S, Bott K. Current status of global cultivated seaweed production and markets. World Aquac 2014;45:32–7.

[15] Valero M, Guillemin M-L, Destombe C, Jacquemin B, Gachon CMM, Badis Y, et al. Perspectives on domestication research for sustainable seaweed aquaculture. Perspect Phycol 2017:33–46.

[16] Dickson R, Ryu J-H, Liu JJ. Optimal plant design for integrated biorefinery producing bioethanol and protein from Saccharina japonica: A superstructure-based approach. Energy 2018;164:1257–70. doi:https://doi.org/10.1016/j.energy.2018.09.00

Copyright © 2019 ICAE