

Forest Biomass-to-biofuel Factory Location Problem with Multiple Objectives Considering Environmental Uncertainties and Social Enterprises

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Abstract

Forest biomass energy enjoys merit of large production, renewability, and clean combustion. However, most related works focused on only the objective of minimization of cost or pollution, but seldom on the social aspect. Social enterprise provides business models that cope with social or environmental problems, e.g., offering employment opportunities in disadvantaged areas. Therefore, this work considers social enterprises and environmental uncertainties in a forest biomass-to-biofuel factory location problem with multiple objectives, which determines whether to open forest biomass-to-biofuel factories at their potential locations to meet the energy demand and other practical constraints. Aside

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from minimization of cost and carbon emissions, the concerned problem additionally considers the objective of maximizing the job offers provided by opening factories from the social enterprise aspect. Additionally, based on the fuzzy theory, this problem includes the following environmental uncertainties: uncertain number of inventory days, uncertain job offers per unit of surplus factory scale, uncertain biomass production amount, and uncertain biofuel demand due to the price fluctuation of fossil fuels. This work employs the GIS to determine candidate locations of acquiring forest biomass and opening factories, and then solves the problem by fuzzy multi-objective linear programming. Through simulation, we observe the conflict among objectives, compare the differences between the proposed method and previous methods, and analyze the key factors that affect practical implementation. Simulation results show that when the total biofuel demand exceeds 200 million liters per year, the proposed method provides 16% more job offers than the previous method that focused on only cost minimization.

Keywords: Facility location problem, biomass-to-biofuel factory, social enterprise, sustainability, fuzzy multi-objective linear programming, fuzzy theory

1. Introduction

The International Energy Agency (IEA) pointed out that, by 2040, the demand of the global energy will increase by one-third of the demand in 2015 (International Energy Agency, 2014), and this would inevitably result in consuming more fossil fuels, which are still the main energy source to the world. Renewable energy is bound to be the future trend of alternative energy sources, which can simultaneously 1) address the growing demand

for fossil fuels, 2) comply with the international greenhouse gas pollution regulations, and 3) mitigate fossil fuel resource depletion. Among renewable energy sources, bioenergy has great potential, and it is the second most important source of energy that is surpassed only by fossil fuels.

Biomass energy has the characteristics of large production, renewability, and clean combustion, so that consumption of fossil fuels can be effectively reduced to meet international regulations of greenhouse gas pollution, and energy can be more cleanly produced. Biomass energy is sourced from biomass (especially, crops), which refer to the organic mass produced by organisms. The range of raw materials of biomass energy includes wood and forestry wastes such as sawdust; crops and agricultural wastes such as soybean pods, corncobs, rice husks, bagasse, etc. The liquid fuel converted from solids consisting of these biomass using chemical methods is called biofuel, which includes the following advantages: 1) providing stable energy, 2) mobilizing social economy and providing job offers, 3) protecting the environment and reducing emissions of pollution of fossil fuels.

The most important thing of acquiring the raw materials for biomass energy (or say, harvesting biomass) is to arrange the biomass harvest facilities and manpower in appropriate locations, to facilitate collection of raw materials for biomass. As the first step to establish and manage an enterprise, the facility location problem (FLP) is to determine the layout and scale of facilities from potential locations as well as the transportation of products, to achieve the objective of minimize cost or maximize profit. The losses caused by inappropriate FLP decisions cannot be improved by subsequent strengthening of management. In recent years, with the increasing attention of bioenergy, the biomass-to-

bioethanol FLP (BBFLP) has also become the target of many works. For instance, Marvin et al. (2012) established a mixed integer linear programming method for solving the BBFLP in a 9-state region in the Midwestern United States; Wilson (2009) developed a software based on GIS to solve the BBFLP that minimizes transportation and farmgate costs; Jenkins and Sutherland (2014) built a mathematical model to find the optimal solutions of the BBFLP that provides the minimum unit cost. Although the BBFLP has been investigated in the previous works, most of these previous works considered only the objective of minimizing cost (or maximizing benefit) or pollution emissions. Few works focused on the objectives raised from the social aspect, so that the profits gained by biomass-to-bioethanol enterprises cannot feedback the society and environment, impacting sustainability of these enterprises.

As the resources have been declining day by day in this world, the gap between rich and poor has gradually worsened under capitalism. Italian economist Pareto observed from the British's wealth-benefit model in 1897 that the richest 20% owns 80% of wealth. The M-form society in developing countries have become a problem that cannot be ignored, of which the problems brought about by the M-form society directly affect the country's social problems of unemployment and crime rates. As greater importance is attached to these social issues, the pursuit of benefits and costs in the past is no longer the best and only objective that is being considered. Aside from pursuing benefits or costs, environmental costs and social costs must be taken into consideration in order to achieve the purpose of sustainable development. Therefore, a new type of business model between pursuit of benefits (or cost) considerations and nonprofit, called social enterprise, has emerged. For instance, Mair and Marti (2006) indicated that the social enterprise is defined

as the tangible outcome of social entrepreneurship. Nicholls (2010) mentioned that the social entrepreneurship is a critical role in terms of resolving conflicting discourses within its future paradigmatic development.

Recently, most countries have discussed the topic of social enterprise in which the boundaries between society and enterprises are blurred. The model of social enterprise is to utilize the benefits gained from enterprises to feedback the society and environment, such as providing job offers or selling goods for the people in disadvantaged areas, and providing services or products related to environmental protection. It does not only keep enterprises in sustainability, but also enhance the financial autonomy of nonprofit organizations. A lot of previous works have pointed out the impact of unemployment to the people in the area where the corporation is located. For instance, unemployment has impact on health status (Sadava et al., 2000); and unemployment has impact on the physiological functions of middle-aged and elderly people (Gallo et al., 2006).

With increasing attention to environmental protection, the paradigm of production management has moved from the end-of-the-pipe treatment (i.e., setting up equipment to process or treat industrial wastes to meet regulations and standards) to cleaner treatments for each stage of the whole production process (including planning, design, production, usage, and disposal of products), in which preventive environmental strategies are continuously employed to increase ecological benefits and reduce the damage to the human and environment. For cleaner production in factories, it has been suggested to use clean energy such as solar power, wind power, hydropower, geothermal energy (Maji, 2019), and bioenergy (Sulaiman et al., 2020) to reduce CO₂ emissions during the production process, and to further mitigate global warming (Danish and Ulucak, 2020). Among clean energies,

bioenergy is generated through burning biomass; and more importantly, it is renewable and circulated. Plants absorb CO₂ in the air through photosynthesis, and their biomass is burned to generate bioenergy to release CO₂ back to the air. Such circulation can avoid extra CO₂ emissions. Another advantage in developing bioenergy is to cope with plant wastes (e.g., wood sawdust, crop residues, and agricultural wastes), which can be recycled to be transformed to biofuels. Therefore, it is beneficial to use bioenergy in cleaner production.

To provide stable production of bioenergy, a lot of previous works have investigated the optimization problems on bioenergy factories and supply chains (including production, storage, and delivery of bioenergy), e.g., maximizing the net present value (NPV) (Hombach et al., 2016) and minimizing the total transportation cost (Castillo-Villar et al., 2017) in bioenergy supply chains. Multiple-objective optimization problems in bioenergy supply chains were also considered, e.g., simultaneously maximizing the NPV and the environmental performance (Murillo-Alvarado et al., 2015); and simultaneously minimizing the production cost and maximizing the biofuel quantity (Mahjoub et al., 2020). Generally, sustainable development involves economic development, environmental protection, and social development. However, a research gap has existed since most of the previous works on bioenergy supply chain management (SCM) only focused on economic and environment aspects but did not consider the aspect of social development. Consequently, to narrow this research gap, this work aims to achieve sustainable development of bioenergy facilities from the three aspects. That is, in addition to economic development and environmental protection of bioenergy facilities, this work additionally considers providing job offers from the aspect of social development.

This work adopts the methodology of fuzzy multi-objective linear programming

(FMOLP) to create a forest biomass-to-biofuel factory location problem (FBFLP) that considers economic, social, and environmental aspects and environmental uncertainties. Aside from economic and environmental objectives, the proposed FBFLP model additionally considers the social-concern objective of maximization of the job offers provided from opening forest biomass-to-biofuel factories (FBF). The model has three objectives: minimization of the total cost (including the harvesting cost, the inventory cost, as well as the energy consumption cost), minimization of the total carbon emissions (including those caused by the quantities harvested at biomass supply locations and transported from biomass supply locations to the FBFs), and maximization of the job offers (including the fixed number of workers, and the average number of workers of each extra unit for the larger scale FBFs). Because the decisions of the FBFLP model could be affected by environmental uncertainties, this work employs the fuzzy theory to address uncertain parameters, and further employs the FMOLP methodology to transform multiple objectives into a single objective value. Then, this work solves the FBFLP model by the CPLEX optimizer. For performance evaluation of this method, we simulated a case study of opening FBFs in Taiwan. Since Forestry Bureau, Taiwan is the major government office for forestry administration in Taiwan, eight forestry business districts from the data of the Forestry Bureau, Taiwan served as the sites of supplying raw materials (i.e., forest biomass), and they were used to simulate 16 candidate FBF locations, in which the relevant geographic information (including road information and factory location coordinates) was acquired through GIS.

The main contributions of this work are given as follows:

- Compared with conventional fossil fuel facilities, FBFs provide clean production of

energy. This work proposes a novel FLP for opening FBFs from economic, environmental, and social aspects, to increase sustainability of FBF enterprises. Specifically, different from previous works on FLPs that focused on only the operating costs and carbon emissions, this work additionally considers the objective of maximizing job offers, inspired from social enterprises, so that the benefits gained by FBF enterprises can feedback the society and environment.

- This work proposes a mathematical programming model for the concerned problem, which provides decision-makers multiple flexible decision alternatives consisting of three objectives (i.e., minimizing the total production cost, minimizing the total carbon emissions, and maximizing the job offers). Based on the concerned importance on each objective, decision-makers can freely set the achievement degree of each objective, so that they can efficiently obtain the results and rapidly adjust their decisions. Especially, if decision makers put more importance on reducing carbon emissions for cleaner production, they can set a higher achievement degree of the corresponding objective.
- This work additionally considers four environmental uncertainties (i.e., uncertain number of inventory days, uncertain job offers per unit of surplus factory scale, uncertain biomass production amount, and uncertain biofuel demand due to the price fluctuation of fossil fuels), and then employs the fuzzy theory to address these uncertainties. Note that this work does not consider the weather uncertainty, and hence may not be suitable for the problem instances with weather uncertainty.

2. Literature review

2.1. FLP

The FLP is to determine the layout and scale of facilities from potential locations as well as the transportation of products, in order to achieve the objective of minimizing cost or maximizing profit. The FLP has been widely employed in various fields and industries. Boonmee et al. (2017) considered the FLP for emergency humanitarian logistics that adopts environmentally and socially-friendly decisions with financial outcomes. Rohaninejad et al. (2018) developed reliable FLPs in multi-echelon networks, and addressed the problem by an accelerated Benders decomposition algorithm. Hajibabai et al. (2014) considered an integrated FLP which concurrently takes into account traffic routing under congestion and pavement rehabilitation so as to minimize the total cost. Coelho et al. (2017) investigated a capacitated FLP for reverse logistics activities, and further established a mixed-integer model for the problem. Ahmadi-Javid et al. (2017) gave a comprehensive survey on the applications of FLPs in healthcare. Toro et al. (2017) jointly considered the FLP and the vehicle routing problem with multiple objectives under environmental impact. Rahmani and MirHassani (2014) adopted a hybrid firefly-genetic algorithm to address the FLP that minimizes the cost. Note that most of the previous works on FLP in various fields considered the objective of minimizing the cost or maximizing the benefit, but few of them investigated the objective raised from social issues.

2.2. Related works on FBFLP

The FBFLP of this work belongs to the forest industry. The source location of raw materials (i.e., forest biomass harvested) has the greatest impact on the facility location

selection result, because the forest resource is a type of raw materials with relatively large volume. Therefore, it must go through a series of processes to be stored in the facility after the trees are logged. The processing must first go through harvesting, pretreatment, loading, transportation, and finally to the FBF for storage. Each step in the process will result in cost increase, pollution emissions, and energy consumption. The processes after storage in the FBFs are the issues of the midstream and downstream levels. Note that Simioni et al. (2018) gave a comprehensive survey on forest biomass chain of production.

Table 1 compares the previous works on FLP for bioenergy plants according to the problem scope, objective, bioenergy type, and methods, in which the first three works that are single-objective are related to the FBFLP concerned in this work.

Table 1. Comparison of the previous works on FLPs for bioenergy facilities.

Reference	Facility type	Objective	Method	GIS
Esnaf et al. (2009)	FBF	Single-objective (cost or pollution)	Fuzzy clustering	No
Zhang et al. (2011)	FBF	Single-objective (cost)	LP	Yes
Zhang et al. (2016)	FBF	Single-objective (cost, pollution)	LP	Yes
Cebi et al. (2016)	Agricultural waste biomass power plant	Multiple-objective (achievement degree)	Fuzzy AHP	No
De Meyer et al. (2015)	Biogas plant	Single-objective (energy)	LP	Yes
Franco et al. (2015)	Biogas plant	Multiple-objective (sustainability)	AHP-FWOD	Yes
Sultana and Kumar (2012)	Bioenergy facility	Single-objective (profit or resource utilization)	AHP, Techno-economic model	Yes
Shu et al. (2017)	Bioenergy plant	Single-objective (welfare)	Agent-based model	No
Costa et al. (2017)	Biodiesel plant	Single-objective (Profitability)	Simulation optimization	No
He-Lambert et al. (2018)	Biorefinery and preprocessing facility	Single-objective (profit)	MIP, two-stage optimization procedure	Yes

Recently, a lot of previous works based on the concept of sustainability explored

bioenergy and biomass-to-biofuel SCM for reducing the environmental pollution caused by fossil fuels. These previous studies considered social responsibility and built mathematical models to simulate suitable locations for the original BBFLP. Nevertheless, to the best of our understanding, they never took optimization of cost, job offers, and environmental pollution in to account at the same time. The previous works that are the most relevant to our problem model are (De Meyer et al., 2015) and (Zhang et al., 2016). Consequently, this work is based upon the above two works to develop an FBFLP model that meets more realistic situations. Furthermore, this work extends the problem model to an FMOLP model based on (Cebi et al., 2016), in which all objectives are converted into an achievement degree of a single objective.

2.3. Social enterprise

The concept of social enterprise first originated in the 1970s. Recently, many developing countries have passed bills to support the development of social enterprise, e.g., B Corporation (USA), Community Interest Company (UK), Low Profit Limited Liability Company (USA), Social Enterprise Promotion Act (South Korea). Cetindamar et al. (2015) explored a corporation that offers a certification. Kimbrell (2013) indicated that the certification of the bills can provide the assistance and support to the same degree of social contribution (e.g., tax incentives, financial financing preferences, no-cost interest-returned, etc., and can also gain the trust of consumers. The social enterprise that passes the bill certification is abbreviated as B Corporation (Benefit Corporation). B corporation upholds the core spirit of triple bottom line. Elkington (1997) proposed the triple bottom line in 1997, subverting the traditional businesses in regarding cost benefits as a single objective in the past. Instead, the objective was suggested to be divided into three parts: corporate

earnings, social responsibility, and environmental responsibility. For instance, Norman and MacDonald (2004) indicated that the idea behind the triple bottom line is to measure the success or health of a corporation by the traditional financial, social/ethical, and environmental performance; Reimers-Hild (2010) presented that the triple bottom line is one of the best markers to assess the sustainability and profitability of a business; Montoya-Torres (2015) expressed that the triple bottom line has been widely used in current research and practice of supply chain management.

Among the objectives of social enterprises, social responsibility is with the most significant impact caused by unemployment rate. Gerdtham and Johannesson (2003) found that the mortality rate of the unemployed is fifty percent higher than that of the employed. Sadava et al. (2000) found that unemployment has a significant impact on health status. Gallo et al. (2006) found that unemployment has a negative impact on the physiological functions of middle-aged and elderly people. From the above, it can be known that a lot of works have pointed out the seriousness of the impact on unemployment to human beings.

In light of the above, it is observed that a good enterprise requires simultaneously considering corporate earnings, social responsibility, and environmental responsibility. However, most of the previous related works only focused on enterprise earnings, but few of them simultaneously considered social responsibility and environmental responsibility. Therefore, this work proposes an FBFLP problem model that simultaneously considers the three objectives emphasized by a social enterprise and environmental uncertainties, and adopts the fuzzy theory to address this problem.

3. Materials and Methods

The framework of the proposed method is illustrated in Figure 1. First of all, Phase 1 generates the geographical information more in line with the real-world conditions through the combination of GIS, e.g., urban border restrictions, traffic road restrictions, urban distribution, coordinates for the source of raw material coordinates, coordinates of facility locations, traffic distance and other information, to simulate a number of candidate facility locations that are more potential to develop FBF in the concerned region. Next, Phase 2 uses the FMOLP model that combines fuzzy theory with multi-objective linear programming (MOLP) to solve this problem. This method is relatively easy in the calculation aspect and can be converted into a linear programming (LP) form to obtain the Pareto optimal solution (Zimmermann, 1978), to provide the basis for decision-makers to make decisions. Since the objective is converted to an achievement degree, it is easier to judge the number of each objective value in the decision, as well as to see the balance between the objectives of multiple conflicts. Finally, the CPLEX optimizer is adopted to solve the model, further to select the optimal FBF location and the scale of the FBF.

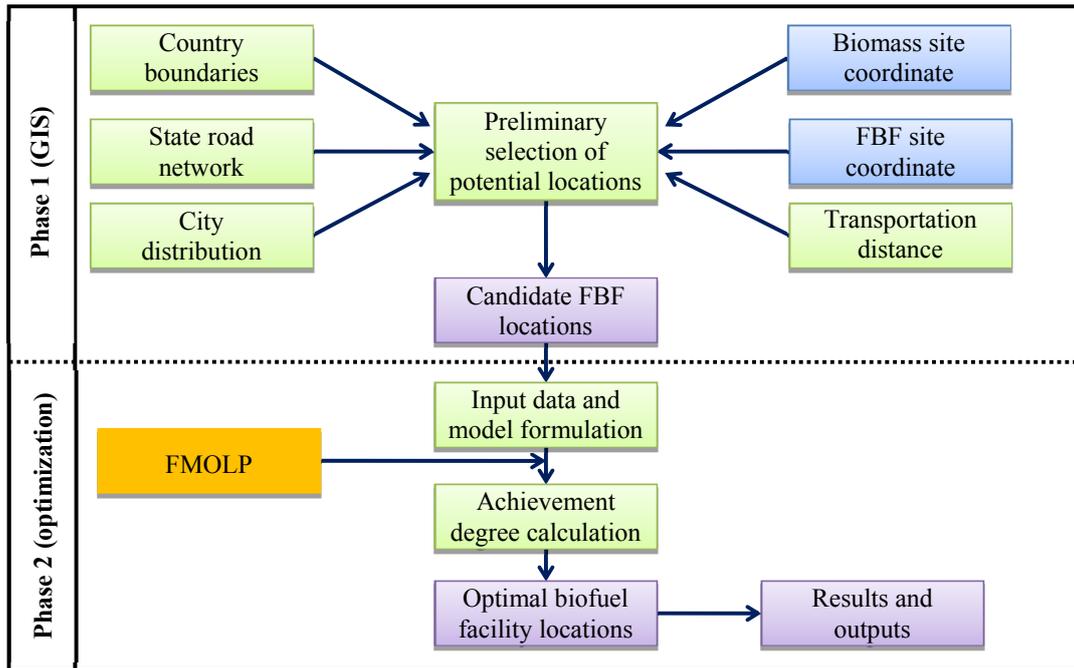


Figure 1. Framework of the proposed method.

In Phase 1, this work attempts to propose a reasonable and satisfactory solution to the FBFLP under the condition of uncertain environmental parameters. This solution is a compromise solution and also an approximation reasoning solution for the reference of decision-makers in the region. This work constructs the problem model as an FMOLP with minimization of total harvesting cost, minimization of carbon emissions, and maximization of job offers as the objectives. The proposed method adopts the fuzzy theory (Zadeh, 1965) to solve the FMOLP. All steps of solving the FMOLP model are given as follows.

- 1) First, we refer to (Zhang et al., 2016) to fuzzificate the uncertain parameters as triangular fuzzy numbers (P, M, O). Note that the triangular fuzzy numbers represent the possible pessimistic values (P), mean values (M), and optimistic values (O) of a certain coefficient.

- 2) This model consists of objective functions and constraints. For the objective functions, the concept of linear membership functions and the max-min method (Zimmermann, 1978) are adopted to convert each objective function to an achievement degree.
- 3) Then, add the achievement degrees of all objectives to obtain the overall achievement degree L . For the constraints of the model, the weighted average method using a beta probability function is adopted to perform defuzzification.
- 4) Finally, use the try-and-error method to improve the overall achievement degree L .

The technical details of the complete mathematical programming model are detailed in Appendix A, including the proposed MOLP model, the proposed FMOLP model, and the technical components that solve this FMOLP model.

4. Results and discussion

4.1. Experimental setting

The proposed FBFLP model is a general model that can solve any FBFLP problem instance on a specific geographical region. However, this model includes some parameters that may not easily be acquired. We have made a lot of effort to acquire the real data in Taiwan, and hence the simulation in this work is conducted on a case study of opening FBFs in Taiwan. Note that it can be extended to solving other large-scale problem instances if their data can be acquired.

The parameters used in the experiments are introduced as follows. This work simulates 8 locations for the suppliers of providing forest biomass raw materials, and also simulates

16 candidate sites for opening FBFs (see Figure 2). About the 8 locations for the suppliers of providing biomass raw materials, this work selects the national forestry business districts established by the Forestry Bureau, Taiwan. Forest land divided is based on factors of woodland, climate, vegetation, and the current status of land use, and is coordinated with the survey data, business objectives, traffic conditions, altitude, wildlife, vegetation and relevant land planning division developed in the national forest district management plan. In Taiwan, the forest districts are classified into four categories: 1) nature reserve district, 2) national land protection and conservation district, 3) forest recreation district, and 4) forest management district. Due to regulations of the Taiwan government, except for the forest management district, logging in other districts are prohibited. Therefore, we choose the forest resources of the forest management district as the source of biomass raw materials in the simulation. Considering the sustainable development, the annual upper bound of using forest biomass cannot be higher than 20% of the forest resources in the forest management district. That is, no more than 20% of the forest resources in the total forest management district can be used each year. The locations of forest biomass raw materials are shown in Figure 2.

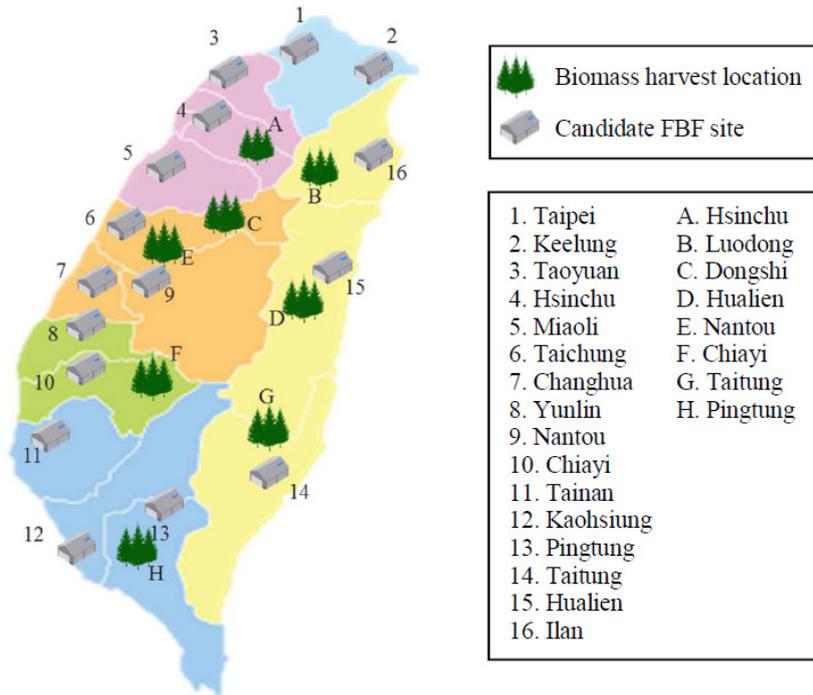


Figure 2. The map of Taiwan with 8 locations of the suppliers of providing biomass raw materials, and 16 candidate sites for opening FBFs.

We refer (Küçük, 1997) to convert the forest area of the original forest management district (hectare) to the forest biomass content provided (ton), as shown in Table 2. Referring to (Ozgen and Gulsun, 2014), this work assumes that 10% to 20% of the upper and lower bounds of the parameter are used as changes caused by the external environment. Consider four fuzzy coefficients for n (i.e., number of inventory days per year), β (i.e., the average job offers per unit of surplus facility scale), b_i (i.e., the upper bound of biomass production), and D (i.e., the total biofuel demand). After defuzzicating these fuzzy coefficients with the weighted average method, n , β , and D are set as shown in Table 3.

Table 2. Forest biomass content of the forest management districts in Taiwan.

Biomass (ton)	Year						
	2009	2010	2011	2012	2013	2014	2015
Hsinchu	636,400	636,734	631,400	631,400	631,400	631,400	631,400
Luodong	402,200	402,200	402,200	402,200	402,200	402,200	402,200
Dongshi	252,334	252,334	252,334	252,334	252,334	252,334	252,334
Hualien	765,400	765,400	765,400	765,400	765,400	372,934	372,934
Nantou	474,000	505,402	505,402	505,402	505,402	505,402	505,402
Chiayi	245,068	245,068	245,068	245,068	245,068	245,068	245,068
Taichung	244,866	244,866	244,866	244,266	244,266	244,266	244,266
Pingtung	1,202,934	1,202,934	1,202,934	1,093,466	1,093,466	1,093,466	1,093,466
Total	4,223,202	4,251,938	4,249,604	4,139,536	4,139,536	3,747,070	3,747,070

Table 3. Parameter setting used in simulation.

Parameter	Notation	Value	Unit
Unit energy consumption cost	α	0.0225	\$/MJ
The cost of pretreating tree stumps	h	13.33	\$/ton
The cost of harvesting tree stumps	s	7.6	\$/ton
The cost of loading and unloading cargos by trucks	t_{lu}	4.10	\$/ton
The cost of the total truck mileage	t_d	0.051	\$/ton-km
The inventory cost per ton of biofuels per year	H	35.17	\$/ton-year
The fixed cost of opening an FBF	F	13.92	M\$
The total number of inventory days in one year	n	120–180	day
Number of FBF operating days	N	365	day
The energy consumed by harvesting each ton of forest biomass	e_h	160	MJ/ton
The energy consumed by trucks	e_{tr}	1.150	MJ/ton-km
The carbon emissions when harvesting forest biomass	g_h	12.79	kg/ton
The carbon emissions from trucks	g_{tr}	0.119	kg/ton-km
Average number of workers provided for each extra unit of FBF scale	β	8–12	person
Total biofuel demand	D	338–524	MLPY

The other fixed parameters in Table 3 are explained as follows. The stump harvesting cost s and stump treatment cost h are referred to (Liao, 2010). Liang and Jheng (2010) mentioned that the total biofuel demand D in Taiwan would reach about 430 (MLPY) in 2015, and the annual inventory cost of biofuel H is \$35.17 per ton each year. It was estimated that if the annual output of bioethanol was 120,000 kiloliters, the number of employment would have increased by 2,614 persons, and the fixed number of employees in the facility would have been 500. After the conversion, each unit (MLPY) of biofuel

production may provide the job offers for about 10 persons. From (Tso, 2011), the estimated cost of constructing a bioethanol facility in Taiwan is approximately 13.92 million dollars. The remaining parameters are not much different between Taiwan and abroad, and therefore, are referred to the parameters provided by (Zhang et al., 2016), as the experimental basis for this model.

4.2. Experimental results

Based on the experimental setting aforementioned, this subsection demonstrates the experimental results of adopting the CPLEX optimizer to solve the concerned FMOLP problem model by the proposed method. The tradeoffs among three objectives (i.e., minimizing cost, minimizing carbon emissions, and maximizing job offers) are concerned in the proposed model. The tradeoffs among the three objectives in the experimental results using the proposed method are given in Table 4. Table 4 includes the optimal solution denoted by ‘Solution 1’ and the other 8 feasible solutions. The decision makers can refer to the objective tradeoffs and their achievement degree requirements to select the best solution from Table 4.

Moreover, if the decision maker does not have any requirement for the three achievement degrees, the current optimal solution (Solution 1) would be selected. However, if a higher achievement degree of job offers is expected (i.e., the social aspect receives more attention), then the decision maker must lose the achievement degrees of the other two objectives. Similarly, if the decision maker emphasizes lower cost and carbon emissions, then he or she must lose the achievement degree of job offers according to the proposed method. It implies that the tradeoff solutions among the three objectives can be

obtained by the proposed method.

Table 4. Tradeoff among the three concerned objectives.

Max $(1/3)\lambda_1+(1/3)\lambda_2+(1/3)\lambda_3$ (i.e., the weights of all objective functions are equal)							
	L	λ_1	λ_2	λ_3	z_1	z_2	z_3
Solution 1	0.394	0.664	0.650	0.393	300,230,032	103,923,620	6,086
$\lambda_1, \lambda_2, \lambda_3$							
Solution 2	0.59	0.633	0.694	0.443	309,536,957	98,345,390	6,298
$\lambda_1, \lambda_2, \lambda_3 \geq 0.394$							
Solution 3	No feasible solution found						
$\lambda_1, \lambda_2, \lambda_3 \geq 0.59$							
Solution 4	0.642	0.678	0.807	0.443	294,994,886	75,672,583	6,298
$\lambda_1, \lambda_2, \lambda_3 \geq 0.443$							
Solution 5	0.644	0.486	0.80	0.643	350,836,436	76,212,411	7,098
$\lambda_3 \geq 0.64$				(max)			
Solution 7	No feasible solution found						
$\lambda_3 \geq 0.65$							
Solution 8	0.695	0.76	0.955	0.44	271,145,891	49,041,032	6,285
$\lambda_1, \lambda_2 \geq 0.7$	(max)		(max)				
Solution 9	0.692	0.77	0.91	0.39	268,528,318	56,418,691	6,100
$\lambda_1 \geq 0.77$		(max)					

If the overall achievement degree L is emphasized, then the decision maker should select the result of Solution 8 (i.e., $L = 0.695$) in Table 4. If increasing the achievement degree of job offers (namely, finding a solution with a higher λ_3 value) is preferred, then the decision maker should select the result of Solution 5 (i.e., $L = 0.644$). We can compare the two solutions to observe the tradeoff among three objectives. An increase of the cost λ_1 value from 0.486 to 0.760 leads to an increase of the L value by 0.5. In addition, it is observed that Solution 8 has the maximal overall achievement degree L , and also has the minimal carbon emissions. In this solution, the FBF scale decreases with minimizing carbon emissions ($\lambda_2 = 0.955$), but it deeply affects the objective achievement degree of job offers λ_3 (leading to a decrease of the λ_3 value from 0.643 to 0.44). A great decrease of

λ_3 also results in a decrease in the L value. Therefore, the tradeoff between the λ_2 value (i.e., carbon emissions) and the λ_3 value (i.e., job offers) exists.

Finally, the solution of the highest overall achievement degree L would be the best decision for this model, and the quantity of biomass transported and the FBF scale in this solution are shown in Table 5. From Table 5, it is suggested to open FBFs at 10 sites (i.e., the candidate FBF sites with nonzero scales in the last column in Table 5), in which the FBFs at 6 sites (i.e., Hsinchu, Yunlin, Kaohsiung, Pingtung, Hualien and Ilan) are on a large scale (equal to 50); and the FBFs at 4 sites (i.e., Taoyuan, Taichung, Chiayi, and Taitung) are on a small scale (between 0 and 50). In addition, from Figure 3, it can be observed that the locations of these opened FBF sites are close to biomass harvest locations, and hence these FBFs can efficiently acquire forest biomass raw materials so as to reduce the transportation cost.

Form Table 5, it can also be observed that FBFs are not suggested to be opened at 6 candidate sites (i.e., Taipei, Keelung, Miaoli, Changhua, Nantou, and Tainan), because their scale in Table 5 is zero, and the quantity of biomass transported to these sites is also zero. From Figure 3, the industrial parks in these sites are farther away from the biomass harvest locations in comparison with other industrial parks, and therefore would result in higher transportation costs.

Table 5. The quantity of biomass transported and the FBF scale in the optimal decision.

Candidate FBF site	The quantity of biomass transported from (ton)								Scale
	Hsinchu	Luodong	Dongshi	Hualien	Nantou	Chiayi	Taitung	Pingtung	
Taipei	0	0	0	0	0	0	0	0	0
Keelung	0	0	0	0	0	0	0	0	0
Taoyuan	224,952	0	0	0	0	0	0	0	32
Hsinchu	357,143	0	0	0	0	0	0	0	50
Miaoli	0	0	0	0	0	0	0	0	0
Taichung	0	0	66,026	0	148,259	0	0	0	30
Changhua	0	0	0	0	0	0	0	0	0
Yunlin	0	0	0	0	357,143	0	0	0	50
Nantou	0	0	0	0	0	0	0	0	0
Chiayi	0	0	0	0	0	245,068	0	0	34
Tainan	0	0	0	0	0	0	0	0	0
Kaohsiung	0	0	0	0	0	0	0	37,143	50
Pingtung	0	0	0	0	0	0	0	357,143	50
Taitung	0	0	0	0	0	0	244,266	0	34
Hualien	0	0	0	357,143	0	0	0	0	50
Ilan	0	357,143	0	0	0	0	0	0	50

4.3. Comparison of different problem instances

Liang and Jheng (2010) estimated that the usage of biomass energy in Taiwan ranged from 270,000 kiloliters to 4,300,000 kiloliters from 2011 to 2015, and seven different biofuel demands are simulated in accordance with this ratio, and compared with (Zhang et al., 2016). The result in (Zhang et al., 2016) is given in Table 6. The result of this work further considers the job offers, and are shown in Table 7. It is observed that the demand values between Tables 6 and 7 have slight differences, because this work considers fuzzy demands but the work in (Zhang et al., 2016) considered fixed demands. That is, the initial input biofuel demands in our model are the same with those in (Zhang et al., 2016), but they are changed after computation of our fuzzy model.

Note that the values for the four critical parameters of our model are further considered in the fuzzy environment (i.e., the total number of inventory days in one year (\tilde{n}), average number of job offers that each extra unit of FBF scale provides ($\tilde{\beta}$), the upper bound of

harvesting biomass at biomass supply location i (\tilde{b}_i), and total biofuel demand \tilde{D}) to extend the MOLP model to the FMOLP mode.

Table 6. The results of (Zhang et al., 2016).

Demand (MLPY)	80	143	206	270	334	397	430
Delivered feedstock cost (million \$)	17.26	31.16	45.844	50.659	57.48	66.578	71.79
Inventory cost (million \$)	29.302	51.227	82.153	100.394	138.64	153.56	179.49
Energy cost (million \$)	2.1839	4.1283	6.235	8.4624	10.738	13.146	15.783
Carbon emissions (million kg)	7.8913	15.139	23.133	31.655	38.398	43.778	47.212
Overall cost (million \$)	48.7459	86.5153	133.232	158.5154	205.858	232.284	265.063
Average cost (\$/ton)	78.437	79.091	79.672	80.119	80.455	80.856	81.354
Average transportation distance (km)	8.15	45.925	46.32	44.5	34.77	49.54	63.03
Job offers (person)	860	1669	2418	3170	3982	4731	5580

Table 7. The result of this work.

Demand (MLPY)	79.67	141.67	204.34	269.5	337	395.67	431.1
Delivered feedstock cost (million \$)	17.355	31.43	46.97	55.49	62.69	67.33	74.79
Inventory cost (million \$)	23.19	55.75	72.71	88.13	108.73	133.56	183.37
Energy cost (million \$)	2.17	4.10	6.94	7.91	9.46	11.14	12.91
Carbon emissions (million kg)	7.85	15.04	26.42	32.91	39.63	44.41	49
Overall cost (million \$)	42.715	91.28	126.62	164.53	205.759	240.03	271.07
Average cost (\$/ton)	78.436	79.058	81.949	84.275	81.284	82.454	83.11
Average transportation distance (km)	8.15	45.925	54.37	34.775	59.7	72.14	80.81
Job offers (person)	859	1665	2973	3590	4611	5467	6300

Next, the differences of the results on cost and job offers in Tables 6 and 7 are further analyzed. The comparison of the results of various costs in this work with (Zhang et al., 2016) is given in Figures 3, 4, 5, and 6. Similar comparison on job offers is given in Figure 7. Comparison between the two results are listed as follows:

- In comparison with (Zhang et al., 2016), the average cost of this work is slightly higher (Figure 3). Note that the average cost includes inventory cost (Figure 4), energy consumption cost (Figure 5), and delivered feedstock cost (Figure 6). This is because this work added the fixed cost of starting an FBF, changed the inventory parameters,

and added the consideration of the job offers objective, so as to result in the increase of cost.

- In terms of inventory cost that is significantly higher than the cost in (Zhang et al., 2016) (Figure 4), since Zhang et al. (2016) only considered cost and carbon emissions, the carbon emission objective affects more on the overall objective value, resulting in choosing to increase of inventory cost so as to reduce the transportation distance.
- In terms of the delivered feedstock cost (Figure 6), the average transportation distance in this work is longer. Since this work takes the job offers into consideration, therefore, more FBFs are opened, resulting in an increase in the average transportation distance and a higher level of carbon emissions at the same time.
- In terms of job offers (Figure 7), when the demand for biomass raw materials is smaller, we do not see much difference. However, when the demand exceeds 200 MLPY, the amount of job offers in this work is apparently better than that in (Zhang et al., 2016). As demand increases, the effect is even more significant.

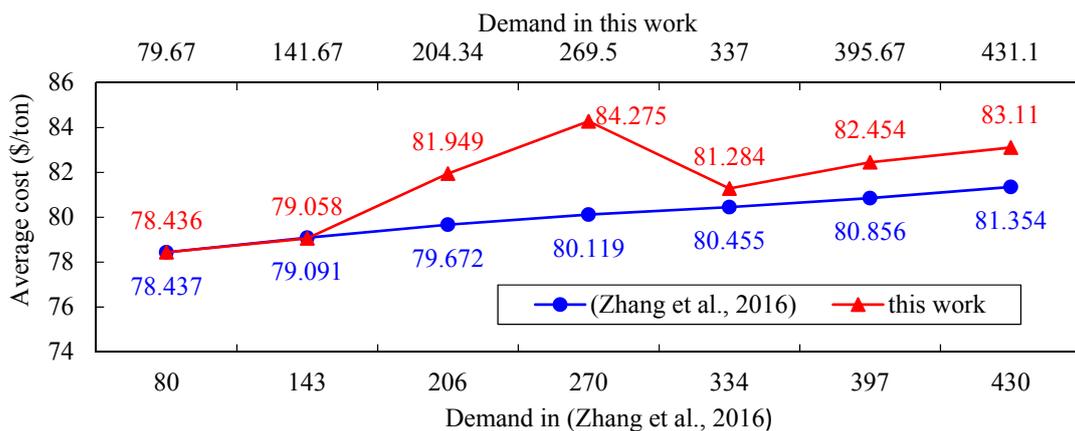


Figure 3. Comparison of the average cost results in this work with (Zhang et al., 2016).

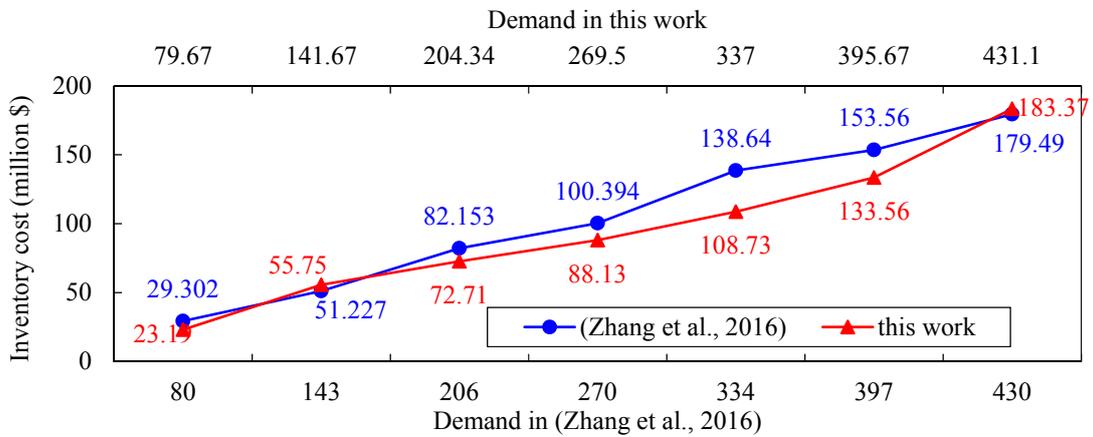


Figure 4. Comparison of the inventory cost results in this work with (Zhang et al., 2016).

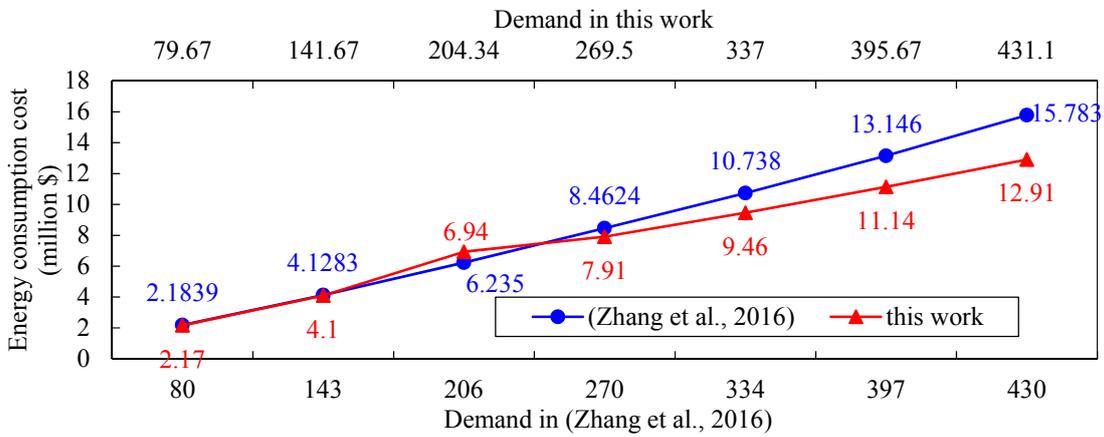


Figure 5. Comparison of the energy consumption cost results in this work with (Zhang et al., 2016).

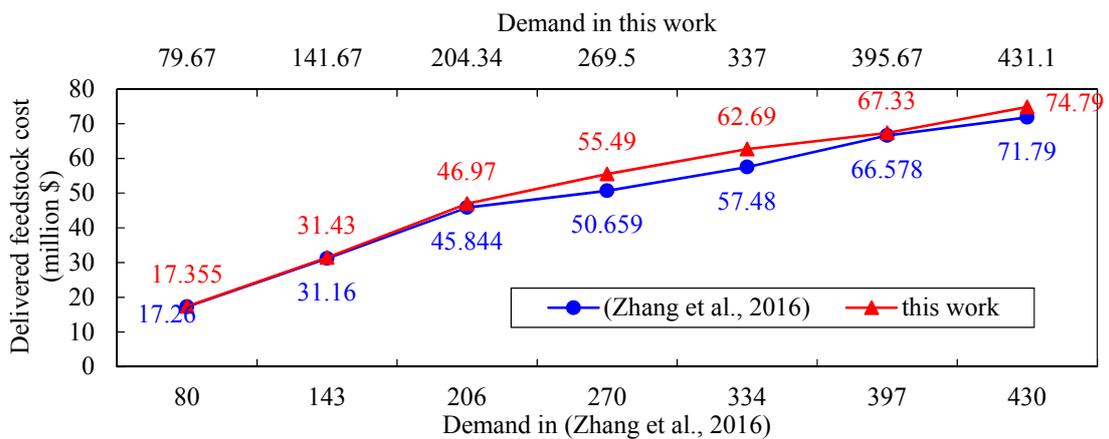


Figure 6. Comparison of the delivered feedstock cost results in this work with (Zhang et al., 2016).

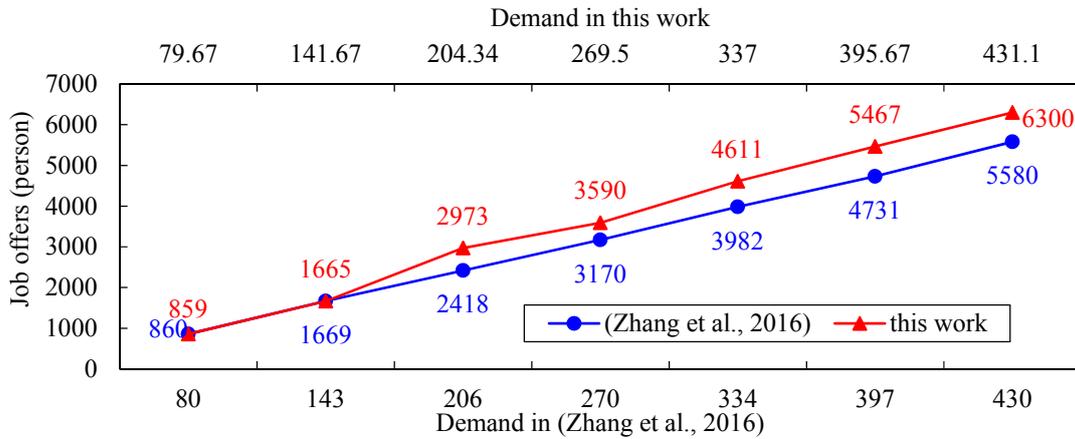


Figure 7. Comparison of the job offer results in this work with (Zhang et al., 2016).

4.4. Comparison of different methods

Under different biomass energy demand simulated in this work, the proposed FMOLP is compared with MOLP and three single-objective linear programming (LP) methods that respectively optimize each of the three objectives (denoted by LP1, LP2, and LP3 for optimizing cost, carbon emissions, and job offers, respectively), as shown in Figures 8, 9, and 10. It is reasonable that the proposed FMOLP does not perform better than all LP methods in terms of cost, carbon emissions, and job offers. But, the proposed FMOLP is relatively stable in terms of overall multi-objective performance. In addition, the decision variables in the best solutions obtained by the LP methods are often biased towards extreme ideal values, but perform poorly in other objectives. In addition, the LP methods can only determine one optimal solution. Therefore, it can be seen that the MOLP and the proposed FMOLP are more suitable to be used in the problems constructed by multi-objectives and are more in line with the actual situation; and the flexibility of choosing solutions is greater. In terms of comparing with the MOLP, the proposed FMOLP adds the uncertainty caused by environmental changes, and uses the fuzzy weighted method to determine parameters,

making the model more in line with the realistic situation. Therefore, it can be seen that the proposed FMOLP is more suitable to be used in the concerned problem than other methods.

In what follows, we observe the tradeoff among LP1, LP2, and LP3 methods. Figure 10 shows the number of job offers obtained by using five methods, in which the LP3 method that maximizes job offers performs better than other methods. Since the LP3 is solved by maximizing the number of job offers, therefore, more FBFs are opened to maximize the job offers. However, more facilities are opened for storage and transportation, causing higher carbon emissions, transportation cost, and storage cost. Therefore, tradeoffs must be made between this objective and LP1, LP2.

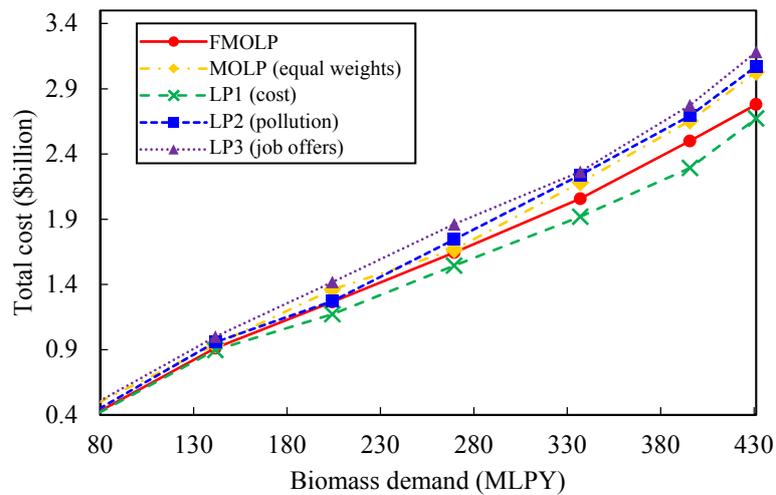


Figure 8. Comparison of total costs using different methods.

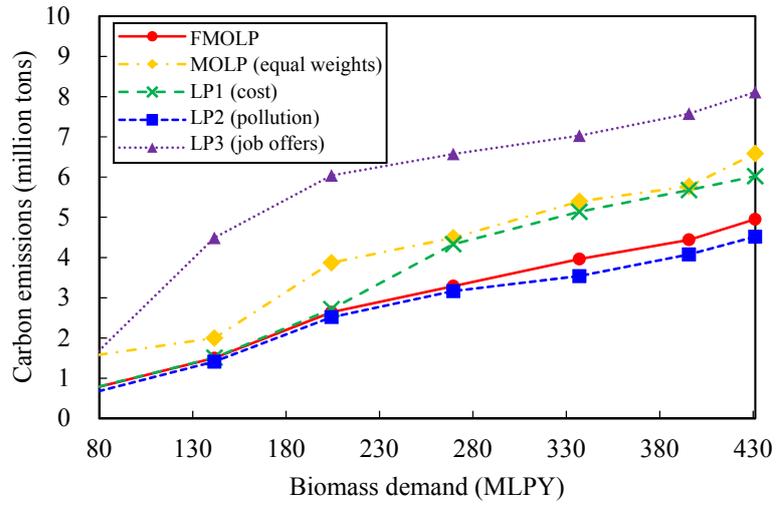


Figure 9. Comparison of carbon emissions using different methods.

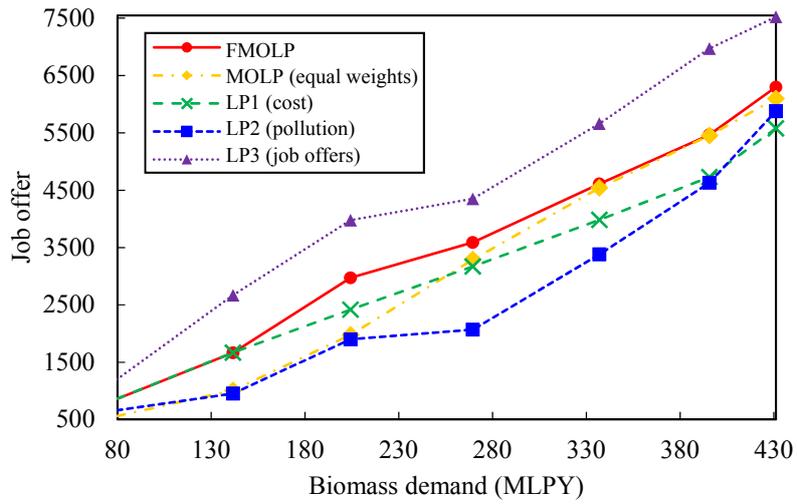


Figure 10. Comparison of job offers using different methods.

From the results on the total cost in Figure 8, we observe that $LP1 < FMOLP < MOLP < LP2 < LP3$. The performance of the proposed FMOLP is significantly better as compared with the MOLP (taking objectives with equal weight) and LP3 (taking job offers as the

objective); and the difference of their costs becomes more obvious with increase of demand for biomass raw materials. For example, when the demand for biomass raw materials is 430 (MLPY), the production cost of the proposed FMOLP decreases by 0.3 to 0.5 billion dollars.

On the other hand, although the performance of the proposed FMOLP is not as good as the LP1 method (taking the total cost as the objective) (Figure 8), a slight increase of the total cost of the proposed FMOLP by the LP1 (Figure 8) drastically reduces carbon emissions (Figure 9) and increases the number of job offers (Figure 10). For example, when the demand for biomass raw materials is 430 (MLPY), the total cost of the proposed FMOLP is 0.1 billion dollars less than the LP1 (Figure 8). But, the carbon emissions of the proposed FMOLP is about 0.1 million tons less than the LP1 (Figure 9), and it provides about 800 job offers more than the LP1 (Figure 10).

We also observe from Figures 9 and 10 that in the carbon emission aspect, $LP2 < FMOLP < LP1 < MOLP < LP3$; and in the job offers aspect, $LP3 > FMOLP > MOLP > LP1 > LP2$. That is, the performance of the proposed FMOLP is ranked the second in each objective. From the above analysis, although the LP1, LP2, and LP3 can obtain the best solution to the objective value of the respective LP, their performance of other objective values is not as good as that of the proposed FMOLP.

Comparing the proposed FMOLP and the MOLP, we can find that the proposed FMOLP considers the fuzzy theory, which is more compliant with the practice than the MOLP. Since the external environment is often in an uncertain situation, it is more reasonable to use the fuzzy weighting method for the parameters of the model. From each objective value, it can be found that the solution obtained by the proposed FMOLP is more

stable than the solution of the MOLP. In order to avoid obtaining too extreme solutions and causing solution instability, it can be seen from this work that the proposed FMOLP has achieved the best solution effect.

5. Conclusion

For environmental protection, each stage throughout the whole production process (including planning, development and design, construction, production, and operation management) requires cleaner treatments. One of the methods of achieving cleaner production is to use bioenergy to reduce CO₂ emissions and further mitigate the global warming. To provide stable production of bioenergy, it is essential to investigate how to optimize the supply chain of bioenergy. However, most of previous works on bioenergy SCM only focused on the production cost, the production quantity of bioenergy, or carbon emissions; but did not consider social enterprises. Therefore, this work has proposed a multi-objective FBF location problem with social enterprise consideration. We first modelled and solved this problem as an FMOLP, and then tested the proposed method on a case study which was simulated for establishing a biomass energy supply chain in Taiwan, in which the fuzzy theory was integrated to simulate the parameters to meet real-world situations. The main difference of this work from previous works that only considered the objectives from the economic aspect (i.e., minimizing cost and carbon emissions) is that the proposed model additionally includes the objective from the social aspect (i.e., maximizing the job offers provided by opening FBFs).

In the future, in order to make FBFs to be more in line with the realistic situation,

although the proposed model has been evaluated in a case study in Taiwan, it would be of future interest to cooperate with other countries to evaluate this model on large-scale problem instances. In addition, it is of interest to consider the weather conditions and natural disasters of Taiwan, because Taiwan has frequent natural disasters such as typhoons and earthquakes, which it may cause uncertain situations in operating days and quantity of raw materials collection. Moreover, more features can be added to enable the decision more in line with the realistic situation, e.g., biomass transportation time, facility area risks, supply competitions, and other features to meet the trend of future SCM. It would also be of interest to further consider optimizing more operations of SCM, e.g., production and distribution of multiple facility layers.

Appendix A.

The subsection builds a mathematical programming model for the concerned problem. This model is modified based on the FBFLP model proposed in (Zhang et al., 2016). Different from most of the previous works that focused on only a single objective to minimize the total cost or maximize the total profit, this work considers multiple objectives (i.e., minimization of the total cost, minimization of the total carbon emission, and maximization of the job offers) while a number of practical constraints are satisfied, so that the profits gained by sustainable biomass-to-biofuel enterprises can feedback the society and environment.

In addition, this work considers four environmental uncertainties (i.e., uncertain number of inventory days, uncertain job offers per unit of surplus factory scale, uncertain

biomass production amount, and uncertain biofuel demand due to the price fluctuation of fossil fuels), and then employs the fuzzy theory to modify the model parameters to meet the real uncertain requirements. Based on the concerned importance on each objective, decision-makers can freely set the achievement degree of each objective, so that they can efficiently obtain the results and rapidly adjust their decisions.

A.1. MOLP model

- Indices:

i : The index for a biomass supply location. Let I denote the set of these indices, i.e., $i \in I$.

j : The index for a candidate location of FBF simulated using GIS. Let J denote the set of these indices, i.e., $j \in J$.

- Parameters:

α : Unit energy consumption cost (\$/MJ).

d_{ij} : The distance from forest biomass supply location i to site j (km).

h : The cost of pretreating tree stumps (\$/ton).

s : The cost of harvesting tree stumps (\$/ton).

t_{lu} : The cost of loading and unloading cargos by trucks (\$/ton).

t_d : The cost of the total truck mileage (\$/ton-km).

H : The inventory cost per ton of biofuels per year (\$/ton-year).

F : The fixed cost of opening an FBF.

n : The total number of inventory days in one year (day).

N : Number of FBF operating days (day).

- r : The rate of converting biomass to biofuel (liter/ton).
- e_h : The energy consumed by harvesting each ton of forest biomass (MJ/ton).
- e_{tr} : The energy consumed by trucks (MJ/ton-km).
- g_h : The carbon emissions when harvesting forest biomass (kg/ton).
- g_{tr} : The carbon emissions from trucks (kg/ton-km).
- J_b : The fixed number of job offers in a facility (person).
- β : Average number of job offers that each extra unit of FBF scale provides (person).
- b_i : The upper bound of harvesting biomass at biomass supply location i (ton/year).
- D : Total biofuel demand (MLPY, million liters per year).

- Variables:

- C_T : Total cost (\$).
- C_H : Total harvesting cost (\$).
- C_{inv} : Biofuel inventory cost (\$).
- E : Total energy consumption (MJ).
- G : Total carbon emissions (kg).
- JC : Total job offers (person).

- Decision Variables:

- q_{ij} : The quantity of forest biomass that is transported from biomass supply location i to the FBF at location j (ton).
- ϕ_j : This binary variable is one if an FBF is opened at candidate location j ; otherwise, it is zero.
- S_j : The scale of the FBF opened at candidate location j (MLPY)

- Objective functions:

$$\text{Minimize } C_T = C_H + C_{\text{inv}} + \alpha \cdot E \quad (1)$$

$$\text{Minimize } G = \sum_{j=1}^J \sum_{i=1}^I (g_h + g_{tr} \cdot d_{ij}) \cdot q_{ij} \quad (2)$$

$$\text{Maximize } JC = \sum_{j=1}^J \phi_j \cdot J_b + (S_j - 30 \cdot \phi_j) \cdot \beta \quad (3)$$

where

$$C_H = \sum_{j=1}^J \sum_{i=1}^I (s + h + t_{lu} + t_d \cdot d_{ij}) \cdot q_{ij} \quad (4)$$

$$C_{\text{inv}} = \sum_{j=1}^J \left[n \cdot (S_j \cdot 10^6 / r \cdot N) - 30 \cdot \phi_j \right] \cdot H + \sum_{j=1}^J \phi_j \cdot F \quad (5)$$

$$E = \sum_{j=1}^J \sum_{i=1}^I (e_h + e_{tr} \cdot d_{ij}) \cdot q_{ij} \quad (6)$$

- Constraints:

$$\sum_{j=1}^J q_{ij} \leq b_i \quad \forall i \quad (7)$$

$$\sum_{i=1}^I q_{ij} = 10^6 \cdot S_j / r \quad \forall j \quad (8)$$

$$\sum_{j=1}^J S_j = D \quad (9)$$

$$q_{ij} \geq 0 \quad \forall i, \forall j \quad (10)$$

$$\phi_j \in (0, 1) \quad \forall j \quad (11)$$

$$30 \cdot \phi_j \leq S_j \leq 50 \cdot \phi_j \quad \forall j \quad (12)$$

The objectives of the model are given in (1)–(3). Objective (1) is to minimize the total cost including the harvesting cost, the inventory cost, as well as the energy consumption cost; and these costs are calculated in (4)–(6). Objective (2) is to minimize the total carbon emissions for the quantities harvested at biomass supply locations and transported from biomass supply locations to the FBFs. Objective (3) is to maximize the total job offers provided by opening FBFs, in which the job offers of this work consider the fixed number of workers, and evaluate the average number of workers of each extra unit for the larger scale FBFs. Equation (4) is used to calculate the harvesting cost, which involves the cost of all harvested biomass (consisting of the harvest cost and the pretreatment cost for tree stumps) and the cost of all transported biomass (consisting of the costs of loading and unloading cargos and the mileage cost for trucks). Equation (5) is used calculate the

inventory cost for the opened FBFs, which includes the fixed cost and the annual average inventory cost of biofuel (i.e., the annual inventory as well as the annual inventory level). Equation (6) is used to calculate the energy cost consumed by trucks and harvesting biomass.

The constraints of the model are given in (7)–(12). Constraint (7) ensures that the total quantity delivered from biomass supply locations to FBFs does not exceed the maximal capacity of harvesting biomass at the biomass supply location. Constraint (8) ensures that the demand for converting biomass to biofuel is satisfied for each the FBFs. Constraint (9) ensures that the annual total biofuel demand is satisfied by the total scale of the opened FBFs. Constraint (10) ensures that the quantity transported from biomass supply locations to the FBFs is non-negative. Constraint (11) enforces the decision variables of the FBF locations are binary. Constraint (12) is used to determine the FBF sites and the FBF scale. Specifically, if an FBF is not opened at candidate location j (i.e., $\phi_j = 0$), then the scale of the FBF opened at candidate site j is zero (i.e., $S_j = 0$), resulting in no fixed cost and no inventory cost from Constraint (5) and no job offers from Constraint (3). Otherwise (i.e., an FBF is opened at candidate site j (i.e., $\phi_j = 1$)), the scale of the FBF opened at candidate site j is nonzero (i.e., $30 \leq S_j \leq 50$). This case leads to fixed cost, and the inventory cost increase with increase of the FBF scale from Constraint (5). In addition, the number of job offers also increases from Constraint (3).

The differences between the model proposed in this work and the previous work (Zhang et al., 2016) are described as follows:

- Zhang et al. (2016) considered only one objective (cost), but this work considers multiple objectives: minimization of cost (1), minimization of carbon emissions (2),

and maximization of job offers (3).

- Zhang et al. (2016) considered carbon emissions as a penalty, but this work considers carbon emissions as a single objective (2).
- This model adds the objective of maximizing job offers (3), which includes the fixed number of job offers of a facility J_b and the average number of job offers β that each extra unit of FBF scale provides. In addition, the number of job offers provided by opening FBFs is restricted to the scale of each FBF by Constraint (12).
- Zhang et al. (2016) did not consider any fuzzy setting. This work considers the fuzzy environments for the four parameters including n , β , b_i , and D to close to the real situation.

A.2. FMOLP model

The subsection explains the FMOLP model based on the proposed MOLP model and the fuzzy theory. The values for the four parameters of the MOLP model (i.e., n , β , b_i , and D) are uncertain in the real situation. Therefore, these critical parameters are further considered in the fuzzy environment (i.e., \tilde{n} , $\tilde{\beta}$, \tilde{b}_i , and \tilde{D}) to extend the MOLP model to the FMOLP mode. The model is developed as follows:

$$\text{Min } C_T = C_H + C_{\text{inv}} + E \cdot \alpha \quad (13)$$

$$\text{Min } G = \sum_{j=1}^J \sum_{i=1}^I (g_h + g_{tr} \cdot d_{ij}) \cdot q_{ij} \quad (14)$$

$$\text{Max } JC = \sum_{j=1}^J (\phi_j \cdot J_b + (S_j - 30 \cdot \phi_j) \cdot \tilde{\beta}) \quad (15)$$

s.t.

$$\sum_{j=1}^J q_{ij} \leq \tilde{b}_i \quad \forall i \quad (16)$$

$$\sum_{i=1}^I q_{ij} = 10^6 \cdot S_j / r \quad \forall j \quad (17)$$

$$\sum_{j=1}^J S_j = \tilde{D} \quad (18)$$

$$q_{ij} \geq 0 \quad \forall i, \forall j \quad (19)$$

$$\phi_j \in \{0, 1\} \quad \forall j \quad (20)$$

$$30 \cdot \phi_j \leq S_j \leq 50 \cdot \phi_j \quad \forall j \quad (21)$$

A.3. Solving the FMOLP model

This work solves the FMOLP model according to the following steps:

Step 1. Apply the max-min method which was proposed in (Zimmermann, 1978) to find the upper and lower bound solutions of the model. We first model the fuzzy coefficients as the triangular fuzzy numbers (P, M, O). The triangular fuzzy numbers represent the possible pessimistic values (P), mean values (M), and optimistic values (O) of a certain coefficient. Let n^O , β^O , b_i^O , and D^O be the optimistic values corresponding to the four fuzzy coefficients \tilde{n} , $\tilde{\beta}$, \tilde{b}_i , and \tilde{D} , respectively. Similarly, n^M , β^M , b_i^M , and D^M are their mean values; and n^P , β^P , b_i^P , and D^P are their pessimistic values. The triangular fuzzy numbers are introduced to the FMOLP model to build the following models with the maximum and minimum objective functions, respectively:

Maximization objective functions:

$$U_1 = \text{Max } C + C_{\text{inv}} + E \cdot \alpha \quad (22)$$

$$U_2 = \text{Max} \sum_{j=1}^J \sum_{i=1}^I (g_h + g_{tr} \cdot d_{ij}) \cdot q_{ij} \quad (23)$$

$$U_3 = \text{Max} \sum_{j=1}^J (\phi_j \cdot J_b + (S_j - 30 \cdot \phi_j) \cdot \beta^0) \quad (24)$$

s.t.

$$\sum_{j=1}^J q_{ij} \leq b_i^0 \quad \forall i \quad (25)$$

$$\sum_{i=1}^I q_{ij} = 10^6 \cdot S_j / r \quad \forall j \quad (26)$$

$$\sum_{j=1}^J S_j = D^0 \quad (27)$$

$$q_{ij} \geq 0 \quad \forall i, \forall j \quad (28)$$

$$\phi_j \in \{0, 1\} \quad \forall j \quad (29)$$

$$30 \cdot \phi_j \leq S_j \leq 50 \cdot \phi_j \quad \forall j \quad (30)$$

Minimization objective functions:

$$L_1 = \text{Min} C + C_{\text{inv}} + E \cdot \alpha \quad (31)$$

$$L_2 = \text{Min} \sum_{j=1}^J \sum_{i=1}^I (g_h + g_{tr} \cdot d_{ij}) \cdot q_{ij} \quad (32)$$

$$L_3 = \text{Min} \sum_{j=1}^J (\phi_j \cdot J_b + (S_j - 30 \cdot \phi_j) \cdot \beta^p) \quad (33)$$

s.t.

$$\sum_{j=1}^J q_{ij} \leq b_i^p \quad \forall i \quad (34)$$

$$\sum_{i=1}^I q_{ij} = 10^6 \cdot S_j / r \quad \forall j \quad (35)$$

$$\sum_{j=1}^J S_j = D^p \quad (36)$$

$$q_{ij} \geq 0 \quad \forall i, \forall j \quad (37)$$

$$\phi_j \in \{0, 1\} \quad \forall j \quad (38)$$

$$30 \cdot \phi_j \leq S_j \leq 50 \cdot \phi_j \quad \forall j \quad (39)$$

Step 2. According to the maximum and minimum objective functions established in Step 1,

U_1, U_2, U_3 represent the upper bounds (maximum values) of the three fuzzy objectives, and L_1, L_2, L_3 represent the lower bounds (minimum values) of the three fuzzy objective functions. Use the upper and lower bounds to establish the following membership functions of the fuzzy maximum and minimum objective objectives, respectively:

$$\mu_i(Z_i(x)) = \begin{cases} 1 & \text{if } Z_i(x) \geq U_i \\ \frac{Z_i(x) - L_i}{U_i - L_i} & \text{if } L_i \leq Z_i(x) \leq U_i \\ 0 & \text{if } Z_i(x) \leq L_i \end{cases} \quad (40)$$

$$\mu_i(Z_i(x)) = \begin{cases} 1 & \text{if } Z_i(x) \leq L_i \\ \frac{U_i - Z_i(x)}{U_i - L_i} & \text{if } L_i \leq Z_i(x) \leq U_i \\ 0 & \text{if } Z_i(x) \geq U_i \end{cases} \quad (41)$$

The above two membership functions are depicted in Figure 11. In the above formula, U_i (resp., L_i) denotes the upper (reps, lower) bounds of the range of the i th fuzzy objective function. The membership function of the objective expresses the degree to which the objective achieves.

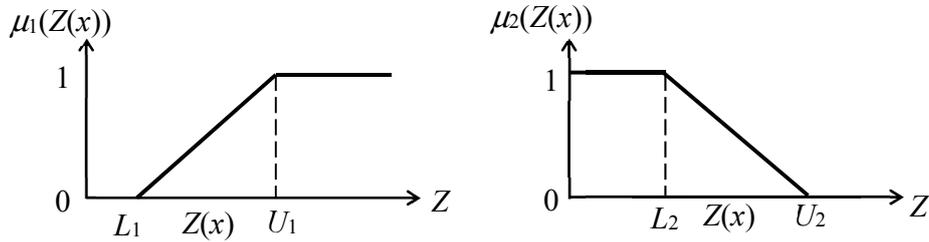


Figure 11. Illustration of the membership functions.

Step 3. Adopt the weighted average method using a beta probability function to defuzzicate the four fuzzy coefficients as follows:

$$\tilde{n} = \left(\frac{1}{6}n^P + \frac{4}{6}n^M + \frac{1}{6}n^O\right)$$

$$\tilde{\beta} = \left(\frac{1}{6}\beta^P + \frac{4}{6}\beta^M + \frac{1}{6}\beta^O\right)$$

$$\tilde{b}_j = \left(\frac{1}{6}b_j^P + \frac{4}{6}b_j^M + \frac{1}{6}b_j^O\right)$$

$$\tilde{D} = \left(\frac{1}{6}D^P + \frac{4}{6}D^M + \frac{1}{6}D^O\right)$$

Step 4. Convert the FMOLY model to the following single-objective crisp model based upon the results at Steps 1–3, in which λ denotes the overall achievement degree. Then, solve the model to obtain a solution.

$$\begin{aligned} & \text{Max } \lambda && (42) \\ & \text{s.t.} \\ & \lambda \leq \mu_k(Z_k(x)) && \forall k \in \{1, 2, 3\} \\ & \sum_{j=1}^J q_{ij} \leq \left(\frac{1}{6}b_j^P + \frac{4}{6}b_j^M + \frac{1}{6}b_j^O\right) && \forall j \\ & \sum_{i=1}^I q_{ij} = 10^6 \cdot S_j / r && \forall j \\ & \sum_{j=1}^J S_j = \left(\frac{1}{6}D^P + \frac{4}{6}D^M + \frac{1}{6}D^O\right) \\ & q_{ij} \geq 0 && \forall i, \forall j \\ & \phi_j \in \{0, 1\} && \forall j \\ & 30 \cdot \phi_j \leq S_j \leq 50 \cdot \phi_j && \forall j \\ & \lambda \in [0, 1] \end{aligned}$$

Step 5. We set the overall achievement degree λ obtained in Step 4 as the threshold of achievement degree in Step 5, then maximize the achievement degree λ_k of the k -th objective for $k \in \{1, 2, 3\}$, and observe whether the achievement degree can be improved.

$$\text{Max } L = \sum_{k=1}^3 w_k \lambda_k \quad (43)$$

s.t.

$$\lambda \leq \lambda_k \leq \mu_k (Z_k(x)) \quad \forall k \in \{1, 2, 3\}$$

$$\sum_{j=1}^J q_{ij} \leq \left(\frac{1}{6}b_j^P + \frac{4}{6}b_j^M + \frac{1}{6}b_j^O\right) \quad \forall j$$

$$\sum_{i=1}^I q_{ij} = 10^6 \cdot S_j / r \quad \forall j$$

$$\sum_{j=1}^J S_j = \left(\frac{1}{6}D^P + \frac{4}{6}D^M + \frac{1}{6}D^O\right)$$

$$q_{ij} \geq 0 \quad \forall i, \forall j$$

$$\phi_j \in \{0, 1\} \quad \forall j$$

$$30 \cdot \phi_j \leq S_j \leq 50 \cdot \phi_j \quad \forall j$$

$$\lambda_k \in [0, 1], \quad w_k \geq 0 \quad \forall k \in \{1, 2, 3\}$$

$$\sum_{k=1}^3 w_k = 1$$

If Step 5 cannot improve the achievement degree, then the achievement degree threshold λ is chosen; otherwise (i.e., the achievement degree can be further improved), λ_k is used as the new achievement degree threshold λ , and then we repeat solving the model until the overall achievement degree cannot be improved, to obtain the best achievement degree of the objective.

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