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Optimal Design of Bioenergy Supply Chains Considering Social Benefits: A Case Study in Northeast China

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Abstract: Bioenergy supply chains can offer social benefits. In most related research, the total number of created jobs is used as the indicator of social benefits. Only a few of them quantify social benefits considering the different impact of economic activities in different locations. In this paper, a new method of measuring the social benefits of bioethanol supply chains is proposed that considers job creation, biomass purchase, and the different impacts of economic activities in different locations. A multi-objective mixed integer linear programming (MILP) model is developed to address the optimal design of a bioethanol supply chain that maximizes both economic and social benefits. The ε-constraint method is employed to solve the model and a set of Pareto-optimal solutions is obtained that shows the relationship between the two objectives. The developed model is applied to case studies in Liaoning Province in Northeast China. Actual data are collected as practical as possible for the feasibility and effectiveness of the results. The results show that the bioethanol supply chain can bring about both economic and social benefits in the given area and offers governments a better and more efficient way to create social benefits. The effect of the government subsidy on enterprises' decisions about economic and social benefits is discussed.

Keywords: social benefits; bioethanol supply chain; multi-objective optimization; China

1. Introduction

With the high-speed of economic growth, China is facing a situation of energy shortage. In 2017, China imported a total of 400 million tons of oil from all over the world, and the ratio of import dependence of oil has grown from 49.0% in 2008 to 65.9% in 2017 [1]. The development of the bioenergy industry will mitigate this situation to a certain extent. Besides the energy shortage, there is another factor prompting China to develop the bioenergy industry: greenhouse gas (GHG) emissions. As the largest producer of carbon emissions in the world, China promised to cut 40–50% GDP unit carbon emissions by 2020 [2]. Bioenergy consumption is nearly carbon-neutral because no carbon from fossil fuel is released into the air [3], which will help with achieving the emissions goal.

The bioenergy industry is also a helpful way to control air pollution. Air pollution is a serious environmental problem in China. Farmers are used to burning agricultural residue (e.g., stover and straw) in farmland after harvesting crops, which is much easier than removing it. Research has shown that burning straw is one of the major causes of air pollution in China, so the substantial reduction of open field straw burning would dramatically improve the air quality [4]. The development of bioenergy industries turns farmers into biomass suppliers. In the bioenergy industry, straw and stover are not burned, but sold to biorefineries as raw materials. Selling biomass could serve as an addition income to the farmers, which has been one of the main concerns of the Chinese government in past decades.

Given the above concerns, the Chinese government has proposed an ambitious plan for the development of bioenergy. In the plan, the output of the bioenergy industry should be no less than the equivalent of 58 million tons of coal by 2020, including 6.8 million tons of liquid fuel such as bioethanol and biodiesel [5].

As for social benefits, it is planned that the development of the bioenergy industry by 2020 will provide four million jobs and increase farmers' income by the billion U.S. dollars every year [5]. The social benefits of bioenergy supply chains have been researched in many studies. However, the social benefits mean much more in China than in other developed countries. Despite decades of rapid economic growth, China is still a developing country. Even in eastern provinces with relatively developed economies, there are many people living in poverty. The development of the bioenergy industry provides a way to reduce poverty and increase household income.

With different configurations of the bioenergy supply chain, the same increase in farmers' income may bring about different social benefits. The same purchase amount of biomass has different effects in developed and impoverished regions and so does job creation. It may offer more social benefits if the created jobs are allocated in impoverished regions or biomass is purchased from the farmers in these regions. Therefore, the design of the bioenergy supply chain has a great impact not only on economic benefits but also on social benefits.

Thus, a comprehensive and practical analysis of economic and social benefits is needed by both enterprises and governments. In this paper, the optimal design of bioethanol supply chains is formulated as a multi-objective mixed integer linear programming (MILP) model, which helps decision makers to ensure the efficiency and effectiveness of biorefinery location, the selection of biomass suppliers, and a transportation network of biomass and products. The objectives are to maximize the economic and social benefits.

A new method of quantifying social benefits is proposed in this paper. In prior research, the main indicator of social benefits was job creation. Based on job creation, more comprehensive measuring models are used for quantifying social benefits in some research. You et al. [6] extended the scope of social benefits beyond job creation and took into account other direct, indirect, and induced economic activities of biofuel supply chains. Some research considered the different impacts of new jobs based on their location [7], in which the social benefits were calculated as the weighted sum of the newly created job and the weights were location-dependent.

In this paper, both the extended scope and the impact factors based on locations are considered. Besides job creation, biomass purchase activities are also accounted for in social benefits. The social benefits are calculated as the weighted sum of job creation and biomass purchase, where the weights are assigned to regions according to their per capita incomes. The core idea of the method is to consider the fact that the same job creation and purchase activity may bring greater social benefits to poorer regions.

A factor that cannot be ignored is uncertainty. The bioenergy industry needs biomass as raw materials. The output of biomass is highly dependent on weather conditions. The biomass availability obviously has a significant impact on biorefinery location, purchasing costs, and transportation costs. Besides biomass availability, the fluctuations in price and demand also affect the benefits of bioethanol supply chains [8]. The model based on the Monte Carlo technology is developed to incorporate uncertainties, in which scenarios are used to reflect uncertainties. The software package CPLEX is employed to solve the model.

The ε-constraint method is employed to solve the multi-objective model and a set of Pareto-optimal solutions are obtained that show the tradeoff between the two objectives. With the Pareto-optimal curve, the relationship between the gain of social benefits and the loss of economic benefits can be observed. The role of government subsidies in decisions about the two objectives is discussed.

The model is applied to case studies in Liaoning, a province in Northeast China. Liaoning has a high level of development in both heavy industry and agriculture and has suitable conditions for developing bioenergy industry.

The rest of this paper is organized as follows. The related literature is briefly reviewed in Section 2. The problem is described in detail and formulated as a multi-objective MILP model in Section 3. The case studies and a discussion are given in Section 4. Conclusions are presented in the last section.

2. Literature Review

In the late 1980s, with the gradual increase of energy prices and the development of bioenergy conversion technologies, the bioenergy industry began to develop rapidly, which led to the development of research into the bioenergy supply chain. Early research focused on the comparison and selection of conversion technologies of biorefineries. Solantausta et al. [9] conducted the initial comparison of the economics of conversion technologies for biorefineries based on different biomass. The production and transportation costs were calculated with the given biomass prices and capital recovery factor. Considering storage, scheduling, and transportation costs, Cundiff et al. [10] formulated an optimal design problem of biomass delivery system as a linear programming model, in which uncertainty was addressed. A decision support system was developed that assisted with the assessment of the techno-economic feasibility of biomass to ethanol schemes in [11]. Various biomass, conversion technologies, and generating cycles were considered in the research. Forsberg [12] used a life cycle inventory as a method to investigate the environmental load of bioenergy transportation chains. In their study, biomass for energy was transported from Sweden to Holland. The result showed that CO_2 emissions from long-range shipping were of minor importance compared to emissions from local bioenergy systems and the long-range transportation did not affect the environmental benefits.

Numerous research studies have been conducted to support the development of the bioenergy supply chain. According to the attributes of the given parameters, models can be categorized into deterministic and stochastic categories. In deterministic models, all parameters are given and deterministic. The optimal design and operation of bioenergy supply chains are formulated deterministically as linear programming [13,14], mixed integer linear programming [15,16], and mixed integer non-linear programming [17]. Deterministic models have been widely used for decades but have limitations because they are too idealistic in that all parameters or constraints have to be known and deterministic. Therefoee, stochastic models are employed to incorporate uncertainties into studies. Awudu and Zhang [18] reviewed stochastic models and uncertainties in research on bioenergy supply chains. Uncertainties are categorized into five groups, including biomass supply uncertainties, transportation and logistics uncertainties, production and operation uncertainties, demand and price uncertainties, and other uncertainties. The Monte Carlo simulation technique was considered an effective means to solve uncertainties [19].

Some research formulates the bioenergy supply chain optimization as a single-objective model in which only the economic benefits, maximization of profits, or minimization of total costs are considered. Dunnett [20] developed a combined production and logistics model to investigate cost-optimal system configurations for biomass supply and bioethanol distribution in which the spatially explicit technique was employed. Kim et al. [21] developed a MILP to maximize the overall profit of the bioenergy supply chain, which enabled the selection of fuel conversion technologies, capacities, biomass locations, and the logistics of transportation.

In addition to economic benefits, the potentials in environmental and social benefits of bioenergy supply chains have been noticed by researchers. McBride et al. [22] defined 19 environmental indicators to support the assessment of the environmental sustainability of bioenergy systems. Numerous studies integrated the environmental and economic objectives to analyze the impacts of bioenergy supply chain, in which the environmental objective was formulated as the maximization of GHG emissions savings [23] or the minimization of GHG emissions [24,25].

Dale et al. [26] identified 16 indicators for assessing the socioeconomic sustainability of bioenergy systems including job creation, an increase in household income, etc. You et al. [6] addressed the optimal design and operations of cellulosic ethanol supply chains under economic, environmental, and social criteria that were measured by the number of local jobs accrued. Job creation was also used to measure the social benefits in [27–29]. Only a few studies considered different levels of impact on jobs created in different locations. Mota et al. [30] proposed a multi-objective model in which the created jobs were more favored in less-developed regions. Cambero and Sowlat [23] incorporated social benefits in multi-objective optimization of bioenergy and biofuel supply chains. The social benefits indicator was calculated based on the weighted sum of all the new jobs created across the supply chain and the assigned weights are based on the preferability of creating each type of job in each location.

Not only job creation, but also buying biomass from farmers contribute to social benefits, and the same purchase account from different regions or the same wages paid to regions may offer different levels of social benefits. To the authors' knowledge, no bioenergy supply chain optimization study has considered both the impact of economic activities other than job creation and the different impact of economic activities on different locations.

3. Description and Model of the Problem

3.1. Problem Description

The problem addressed in this study can be described as follows. The area to be analyzed is divided into regions according to the administrative divisions and each region is deemed as a node that may have three roles in the problem. First, it is a potential biomass supplier with a supply capacity related to the yield of corn and rice. The supply capacity is uncertain since it is significantly affected by weather conditions. The biomass, such as stover and straw, needs to be collected, dried, and stored before being transported to biorefineries. Therefore, if a node is selected to be a biomass supplier, a collection station has to be built. The fixed cost of the facility construction and the variable cost of collecting unit biomass are known. Collection stations bring social benefits to regions by purchasing biomass and job creation.

A node is also a customer that represents bioethanol demand. The demand and price are affected by population, development levels, and macroeconomic situations. Thus, the demand and the price of nodes are both considered uncertain.

Lastly, a node is a candidate location of biorefineries. The biorefinery location is the most important decision in the optimal design, influencing all the other decisions. The biorefinery location affects the social benefits caused by the created jobs since the weight is decided by biorefinery locations. This is also true for supplier selection and collection station location. The weights are related to regional per capita income and how to decide the weights is described in Section 4.

Besides the facility location, the conversion technology and scale of each biorefinery are to be determined as well. The number of created jobs, the conversion rate, and the unit production cost are all influenced by the selection of conversion technologies and scales.

The bioethanol supply chain addressed in this paper is shown in Figure 1, which has three levels: collection stations, biorefineries, and customers. Biomass and bioethanol are transported among levels of the supply chain by road freight. Due to density, risk, and other factors, biomass and bioethanol have different unit freight rates. The model has two objectives to maximize: the economic and social benefits. The former is measured by calculating the difference between the revenue and the total cost. The revenue comes from the price times the fulfilled demand and the total cost consists of six components, including (1) the annualized cost for facility constructions; (2) the purchase cost of biomass; (3) the loading and transportation cost of biomass; (4) the cost of collecting biomass in collection stations; (5) the production cost in biorefineries; and (6) the transportation costs of bioethanol. The definitions of the average total cost and its components are given by Equations (3)–(10). The social benefits are measured by the weighted sum of the purchase expenditure and the salary expenditure in collection stations and biorefineries.

Prior studies usually use the total number of created jobs, the weighted sum of job hours in [7], or the number of equivalent jobs of all economic activities in [6] as one of the indicators of social benefits. All these indicators are not used in this study; instead, the total wages are used because the total social benefits also involve the purchase of biomass. If the number of created jobs or job hours is used as one of two indicators of the social benefits and the purchase of biomass is the other indicator, weights are needed to integrate the two indicators to measure the total amount of the social benefits because their units are inconsistent. Compared to setting weights for the integration of the indicators with different units, it is easier and more feasible to use the sum of expenditures of salary and purchase of biomass as the indicator of the social benefits because they are all calculated in terms of money. Although weights are not needed to unify indicators of different units, the weights are used to differentiate the impacts of the same economic activities on social benefits to different regions.

With the objectives, the decisions to be made include (1) biorefinery location, (2) selection of conversion technologies, (3) selection of scales of biorefinery, (4) selection of biomass suppliers, (5) production of bioethanol, and (6) transportation among nodes.

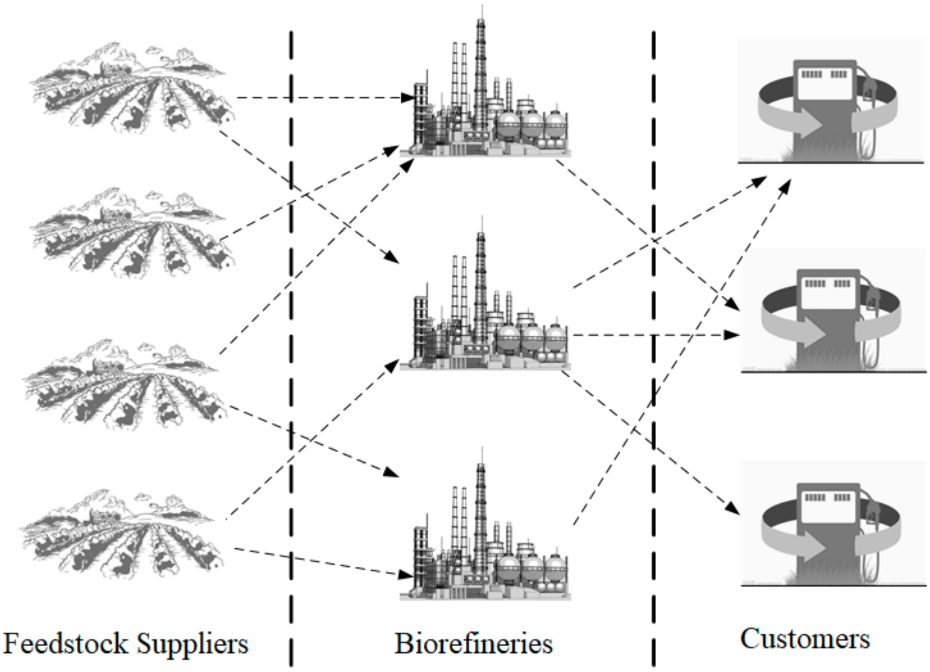


Figure 1. General framework of bioenergy supply chain.

3.2. Model of the Problem

Parameters will be introduced when used. Indices, sets, and decision variables are given as follows.

Indices/sets

N	set of nodes
i	index of candidate locations for biomass suppliers, $i \in N$
j	index of candidate locations for biorefineries, $j \in N$
m	index of demand zones, $m \in N$
R	set of biomass type, indexed by $r \in R$
L	set of scales of biorefineries, indexed by $l \in L$
T	set of conversion technologies, indexed by $t \in T$

S set of scenarios, indexed by $s \in S$

Decision variables

B_{irs} the amount of biomass r purchased from supplier i in scenario s
TQ_{ijrs}^{BM} the amount of biomass r transported from i to j in scenario s
TQ_{jms}^{BF} the amount of bioethanol transported from j to m in scenario s
W_{jrlts} the amount of biomass r converted in biorefinery j with scale l and technology t in scenario s
V_{js} the amount of bioethanol output in biorefinery j in scenario s
ZC_i binary: 1, if a collection station is to be built at i; 0, otherwise
ZR_{jlt} binary: 1, if a biorefinery with scale l and technology t is to be built at j; 0, otherwise

3.3. Economic Objective: Maximizing Annualized Profit

$$\max AverageRevenue - AverageCost \tag{1}$$

where

$$AverageRevenue = \frac{1}{|S|}\sum\nolimits_{jms} P_{ms} \cdot TQ_{jms}^{BF} \tag{2}$$

$$Average^{Cost} = C^{AnnualizedFix} + C^{PurBM} + C^{TranBM} + C^{CS} + C^{Prod} + C^{TranBF} \tag{3}$$

The economic objective is to maximize the total net profit in Equation (1). The revenue is earned by fulfilling the demand of customers. The average revenue is calculated as the sum of revenues in all scenarios divided by the number of scenarios as shown in Equation (2), where P_{ms} is the price of bioethanol of demand zone m in scenario s. The average total cost and its components are given in Equation (3). The average total cost is the sum of annualized fixed costs for the constructions of biorefineries and collection stations $C^{AnnualizedFix}$, the average cost of purchasing biomass for all scenarios C^{PurBM}, the average cost of transporting biomass from collection stations to biorefineries C^{TranBM} and bioethanol from biorefineries to customers C^{TranBF}, the average operation cost of collection stations C^{CS}, and the average cost of converting biomass into bioethanol C^{Prod}.

The annualized fix cost for constructions is given in Equation (4):

$$C^{AnnualizedFix} = \frac{IR}{1 - \frac{1}{(1+IR)^P}} \cdot FC, \tag{4}$$

where IR is the discount rate, P is the project lifetime in terms of years and FC is the total cost for facility constructions and calculated in Equation (5).

$$FC = \sum\nolimits_i ic_i \cdot ZC_i + \sum\nolimits_{jtl} ic_{jlt} \cdot ZR_{jlt}, \tag{5}$$

where ic_i is the construction cost of building a collection station in i, and ic_{jlt} is the construction cost of building a biorefinery in j with scale l and conversion technology t.

$$C^{PurBM} = \frac{1}{|S|}\sum_{irs} c_{ir}^{BM} \cdot B_{irs}, \tag{6}$$

where c_{ir}^{BM} is the cost of purchasing unit biomass r in supplier i.

$$C^{TranBM} = \frac{1}{|S|}\sum\nolimits_{ijrs} (c_{ir}^{Load} + c_{ijr}^{Tran}) \cdot TQ_{ijrs}^{BM}, \tag{7}$$

where c_{ir}^{Load} is the cost of loading unit biomass r in supplier i and c_{ijr}^{Tran} is the cost of transporting unit biomass r from supplier i to biorefinery j.

$$C^{CS} = \frac{1}{|S|}\sum\nolimits_{ijrs} c_{ir}^{Col} \cdot TQ_{ijrs}^{BM}, \tag{8}$$

where c_{ir}^{Col} is the operation cost of collecting unit biomass r in supplier i.

$$C^{Prod} = \frac{1}{|S|}\sum\nolimits_{jrlts} c_{jrlt}^{Prod} \cdot W_{jrlts}, \tag{9}$$

where c_{jrlt}^{Prod} is the production cost of converting biomass r with conversion technology t and scale l in biorefinery j.

$$C^{TranBF} = \frac{1}{|S|}\sum\nolimits_{jms} c_{jm}^{Tran} \cdot TQ_{jms}^{BF}, \tag{10}$$

where c_{jm}^{Tran} is the cost of transporting unit bioethanol from biorefinery j to customer m.

3.4. Social Objective: Maximizing the Social Benefits Measured by the Weighted Sum of Wages of Jobs Created and Expenditure of Purchasing Biomass

$$\max SocialBenefits^{TotalWages} + SocialBenefits^{PurBM}, \tag{11}$$

where

$$SocialBenefits^{TotalWages} = \frac{1}{|S|}\Big(\sum\nolimits_{irs} \beta_i \cdot b_{ir}^{WCol} \cdot B_{irs} + \sum\nolimits_{jrlts} \beta_j \cdot b_{jtl}^{WConv} \cdot W_{jrlts}\Big) \tag{12}$$

$$SocialBenefits^{PurBM} = \frac{1}{|S|}\Big(\sum\nolimits_{irs} \beta_i \cdot c_{ir}^{BM} \cdot B_{irs}\Big), \tag{13}$$

b_{ir}^{WCol} is the salary expenditure of collecting unit biomass r in station I and b_{jtl}^{WConv} is the salary expenditure of converting unit biomass in a biorefinery with scale l and technology t in j. β_i and β_j are the weights of node i or j for the impact of economic activities on social benefits. The value of β_i and β_j are related to regional per capita income. The regions with lower per capita income have larger weights. $\beta_i = \beta_j$, when $i = j$.

3.5. Constraints

$$B_{irs} \le yd_{irs}, \quad \forall i, r, s \tag{14}$$

$$B_{irs} \le M \cdot ZC_i, \quad \forall i, r, s \tag{15}$$

$$\sum\nolimits_{j} TQ_{ijrs}^{BM} \le B_{irs}, \quad \forall i, r, s \tag{16}$$

$$\sum\nolimits_{jr} TQ_{ijrs}^{BM} \le cap^{Col}, \quad \forall i, s \tag{17}$$

yd_{irs} is the available amount of biomass r in supplier i in scenario s. Equation (14) assures the purchase amount of biomass is no more than its available amount. M is a sufficiently large number and Equation (15) indicates that biomass cannot be purchased where no collection station is built. Equation (16) assures the total amount of biomass r transported to all biorefineries does not exceed the purchase amount. Equation (17) assures that the amount of transportation from collection stations does not exceed the capacity limitation of stations.

$$W_{jrtls} \le M \cdot ZR_{jtl} \quad \forall j, r, t, l, s \tag{18}$$

$$W_{jrlts} \le \sum\nolimits_{i} TQ_{ijrs}^{BM} \quad \forall j, r, t, l, s \tag{19}$$

$$V_{js} \le \sum\nolimits_{r} \mu_{rlt}^{Conv} \cdot W_{jrtls} \quad \forall j, r, t, l, s \tag{20}$$

$$V_{js} \leq \sum\nolimits_{l} cap_l^{Rf} \cdot ZR_{jtl} \qquad \forall j, t, l, s \tag{21}$$

$$V_{js} \geq \sum\nolimits_{l} \theta_l \cdot cap_l^{Rf} \cdot ZR_{jtl} \qquad \forall j, t, l, s \tag{22}$$

Equation (18) indicates that a biorefinery can only produce with the designated scale and technology. Of course, no production is allowed if no biorefinery is built. Equation (19) is the mass balance constraint in biorefineries. The right-hand is the sum of the amount of biomass r transported to biorefinery j from all suppliers in scenario s. The left-hand is the amount of biomass r to be used in biorefinery j with scale l and technology t in scenario s. Equation (20) is the mass balance constraint in production, where μ_{rlt}^{Conv} is the conversion factor from biomass r to bioethanol with the selected scale and technology. Equations (21) and (22) define the maximum and minimum annual production capacity, where cap_l^{Rf} is the production capacity of biorefineries with scale l and θ_l is the minimum production amount as a percentage of capacity.

$$\sum\nolimits_{m} TQ_{jms}^{BF} \leq V_{js}, \qquad \forall j, s \tag{23}$$

$$\sum\nolimits_{j} TQ_{jms}^{BF} \leq d_{ms}, \qquad \forall m, s \tag{24}$$

Equation (23) assures the amount of bioethanol transported to customers from biorefinery j in scenario s does not exceed the output of the biorefinery. Equation (24) ensures the amount of the bioethanol transported to customers does not exceed customers' demand.

$$\sum\nolimits_{tl} ZR_{jtl} \leq 1, \qquad \forall j \tag{25}$$

Equation (25) indicates that at most one configuration of scale and technology can be selected for a biorefinery.

4. Case Study and Discussion

The developed multi-objective model is applied to case studies in Liaoning Province, located in Northeastern China. The province has a high energy demand and its agriculture is quite developed. The chief agricultural products in this area are corn and rice. The good accessibility of biomass provides the foundation for developing the bioenergy industry. As a developed province, Liaoning Province has a good transportation infrastructure.

The model is coded in CPLEX Studio 12.6.1 and solved by the same optimization software package. All the computational studies were performed on a Lenovo L440 laptop with Intel i7-4712MQ CPU and 8 GB RAM.

4.1. Input Data

Sources of parameters can be categorized into three types. The first type is parameters that can be found precisely in references such as availabilities of local biomass, distances among nodes, etc. The second type of parameter is obtained through conducting investigations into, e.g., the transportation costs of biomass and bioethanol from local transportation companies. The rest of the parameters are approximated from various literature sources.

As described above, the case studies are conducted for Liaoning Province which comprises 14 cities. Each city is considered a node. A map of Liaoning is presented in Figure 2.

The distance between each pair of adjacent cities is obtained from the Liaoning Province Atlas [31] and the distance between each pair of any two cities is calculated using the shortest path method. The unit transportation costs of biomass and bioethanol are obtained from the weekly report of road freight index issued by China Federation of Logistics and Purchasing [32] and the investigation to local transportation companies. The parameters of transportation costs are presented in Table 1, including the unit transportation cost of biomass from collection stations to biorefineries, the unit loading cost of biomass in collection stations, and the unit transportation cost of bioethanol from biorefineries to customers.

Figure 2. Map of Liaoning Province.

The Monte Carlo technology is employed to incorporate uncertainties in the optimization of the bioethanol supply chain, in which 100 scenarios are generated and used to reflect the fluctuations of uncertain parameters, such as the available amount of biomass, the demand of customers, and the price of bioethanol. With statistical yearbooks [33], the annual gasoline consumption of each city in the past 10 years can be obtained. In 2017, an implementation plan of promoting the mandatory use of bioethanol gasoline for vehicles was issued by the National Energy Administration of China [34], in which gasoline with 10% bioethanol content will be used nationwide by 2020. With this ratio, the bioethanol consumption of the past 10 years can be calculated. Based on the historical data, bioethanol demands of each city are generated for scenarios, assuming the demand follows the normal distribution. The bioethanol demands of each city are presented in Figure 3a.

Table 1. Parameters of transportation costs.

Parameters	Value ($)
Biomass transportation cost	0.15 $ton^{-1} \cdot km^{-1}$
Biomass loading cost	4.38 ton^{-1}
Bioethanol transportation cost	0.29 $ton^{-1} \cdot km^{-1}$

The price of bioethanol in China is not determined by the energy market but set to 0.911 times the price of petrol (92 RON) which is adjusted by the Chinese government regularly [35]. The prices of bioethanol in the case studies are generated based on the historical prices.

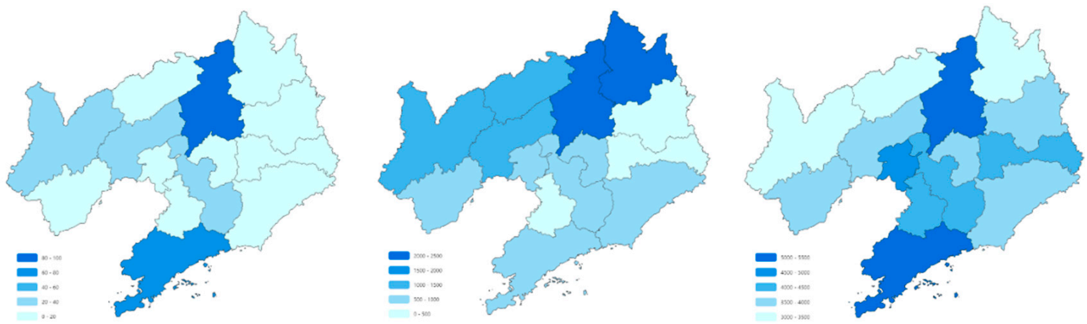
Both the prices and the available amount of biomass belong to the first type of parameters. The yield of corn and rice can be obtained from Liaoning Province Yearbook of Statistical [33]. The available amount of stover and straw can be calculated by the ratio between corn/rice and stover/straw. The price of biomass can be found in the authors' previous work [36]. The total amounts of stover and straw available in the regions are presented in Figure 3b.

There is only one size for collection stations. The fixed construction cost and variable cost for collecting unit biomass are obtained from an investigation to a bioethanol producer. The construction cost of collection stations is \$120,000, and the collecting cost for stover and straw is \$12.9 per ton.

The conversion technology used in the existing bioenergy industry in China is mainly a first-generation technology that converts corns into bioethanol. Because first-generation conversion technology consumes a large amount of food, it has been limited by the Chinese government which decided to promote the development of cellulose bioenergy. Third-generation technology is able to convert cellulose and woody biomass into bioethanol. Given that Liaoning is a developed area in agriculture and does not have many forests, technologies suitable for woody biomass are excluded from consideration and simultaneous saccharification and fermentation conversion is the only technology considered in the case studies. The techonomic parameters of biorefinery of two scales, 45 million gallons per year (MGY) and 80 MGY, are obtained from You et al. [6] and the Aspen Plus process model.

The wages for producing unit bioethanol are obtained by administering questionnaires to the bioethanol producer and investigating the annual reports of listed companies. The wage for collecting unit biomass is obtained from questionnaires as well. The wage for collecting unit biomass is different from the costs of collecting and loading biomass which include labor costs, equipment costs, and other material costs. The gathered data are averaged and adjusted, considering income differences among provinces. The wages for producing unit bioethanol are \$17.42 per ton in a large-scale biorefinery and \$18.32 in a small one. The wage for collecting unit biomass is \$7.3 per ton.

The social benefit weights are related to regional per capita income, PC_i, which can be obtained from the yearbooks [33]. Let $\overline{PC}$ denote the value of the lowest per capita income. The weight of the region i is calculated as $\beta_i = \overline{PC}/PC_i$. The values of regional per capita income are presented in Figure 3c.



(**a**) (**b**) (**c**)

Figure 3. Data of regions: (**a**) the demand for bioethanol (thousands of tons); (**b**) the available amount of biomass (thousands of tons); (**c**) per capita income (\$).

4.2. Case Studies

In this subsection, two case studies considering only economic benefits are conducted. Both case studies pursue profit maximization. The difference is that the supply chain does not have to meet all the demand in the first one and all demand must be met in the second.

4.2.1. Case Study 1: Bioethanol Supply Does Not Have to Meet all the Demand

In such conditions, the model with the economic objective in Equation (1) and meeting constraints (14)–(25) is solved. The optimal net profit is found to be \$36,355,293. The total revenue and cost are $347,355,880 and $311,000,586, respectively, where the profit margin is 10.47%. The percentages of components in the total cost are shown in Figure 4. The production cost accounts for the largest proportion of the total cost, 42%. The rest (58%) consists of the annualized construction cost (11%), the total transportation cost (14%), the total cost of purchasing biomass (21%), and the cost of collection stations (12%).

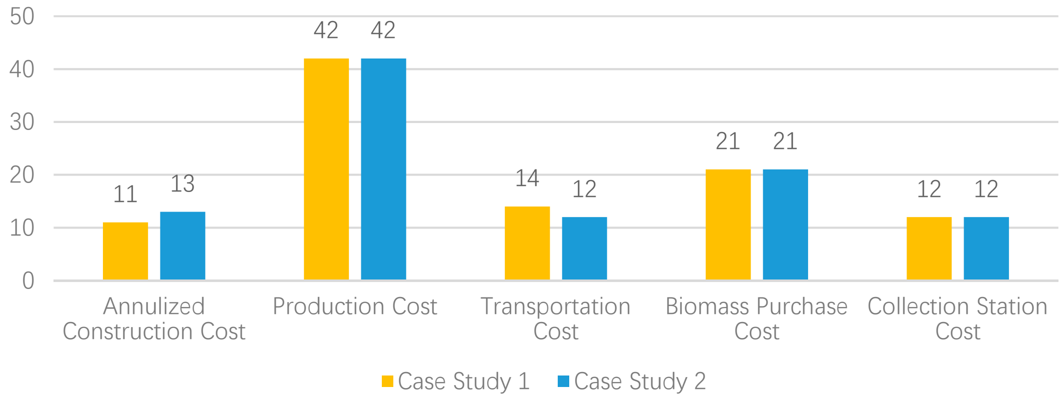
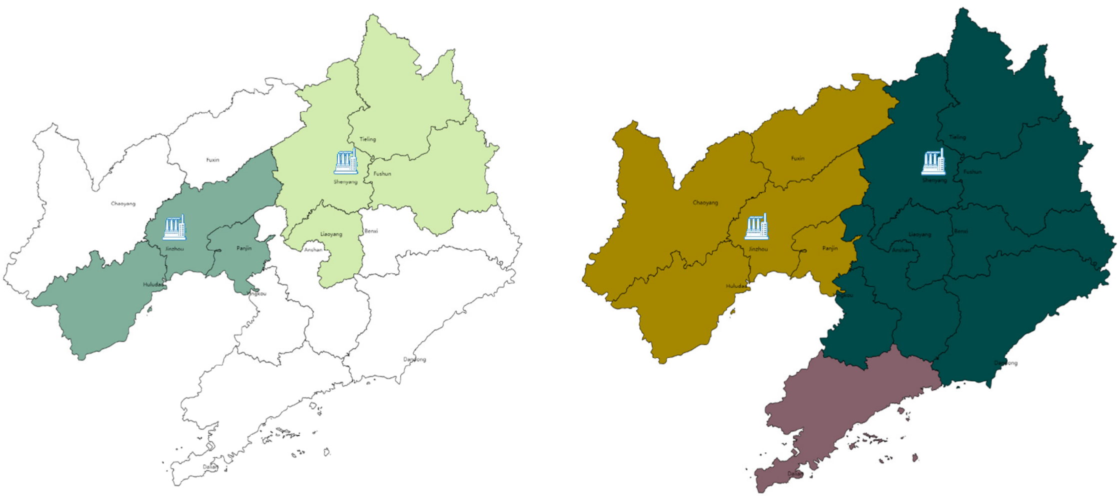


Figure 4. Comparison of cost breakdown between the two case studies.

The biorefineries' locations and the supply of biomass and bioethanol are shown in Figure 5. A large-scale biorefinery and a small one are located in Shenyang and Jinzhou, respectively. The average demand of all scenarios is 368,200 tons and the minimum and maximum total demand in all scenarios are 352,000 and 389,100 tons, respectively. The sum of the production capacity of large-and small-scale biorefineries is 373,300 tons. In most scenarios, all demand is met, but in a few scenarios, not all demand is met because of the fluctuation in demand. Dalian, a city at the end of a peninsula and far away from other cities, had its demand fulfilled in 79 scenarios, and not fulfilled in 21 scenarios. Since it is not required to meet all demand in all scenarios, the decision of the biorefineries is acceptable.



(**a**) (**b**)

Figure 5. Bioethanol supply chain in Case Study 1. (**a**) Selected biomass supplier; (**b**) customer regions supplied by biorefineries.

Shenyang is the economic and geographical center of Liaoning, has the most bioethanol demand, and is the second-largest grain producer, behind Tieling. It is quite reasonable to locate a large-scale biorefinery in Shenyang. Jinzhou has the fifth-greatest demand for bioethanol and is the third-largest grain producer in Liaoning. Jinzhou is also in a relatively central position and borders on six other cities.

Two biorefineries and their biomass suppliers can be seen in Figure 5a, and the customers supplied by the biorefineries can be seen in Figure 5b, where the region in the third color is the bioethanol supplied by both biorefineries simultaneously.

4.2.2. Case Study 2: Demand of all Nodes Needs to be Fully Met

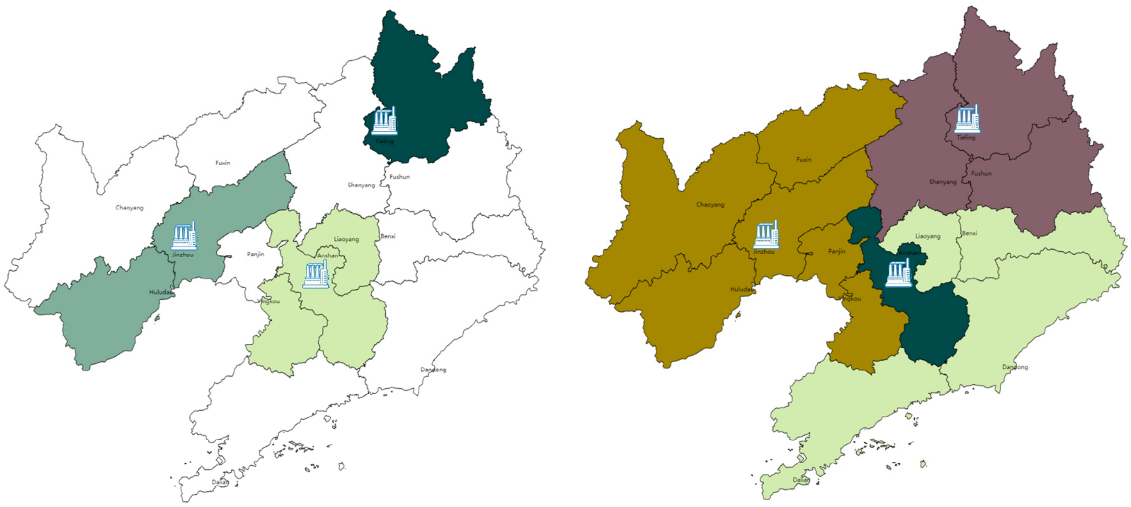
China has launched a series of bioenergy development plans, one of which is to promote the mandatory use of bioethanol gasoline in future. With this prospect, a case study is conducted with a new constraint, Equation (26) taking place of Equation (24), which means in all scenarios the demand of all nodes needs to be fully met.

$$\sum_j TQ_{jms}^{BF} = d_{ms} \qquad \forall m, s \tag{26}$$

Solving the updated model with the economic objective function and constraints (14)–(23), (25)–(26), in the optimal solution, three small-scale biorefineries are to be constructed, in Anshan, Jinzhou, and Tieling, as shown in Figure 6a. The supply regions of three biorefineries are presented in Figure 6b. The regions in the fourth color are the bioethanol supplied by two biorefineries simultaneously.

Since it is required to meet all demand in all scenarios and large-and small-scale biorefineries are not able to supply enough bioethanol, two large-scale or three small-scale biorefineries are needed. Both options can meet the bioethanol demand. The first option has a lower unit production cost but needs more total investment than the second. Adding a biorefinery can make biorefineries closer to the biomass suppliers and customers, thereby reducing the total transportation costs. Given these parameters, the second option has the lower total cost.

The optimal net profit is found to be \$35,979,126 and the total revenue and total cost are \$348,307,766 and \$312,328,640, respectively, where the profit margin is 10.33%. The percentages of components in the total cost and the comparison with Case Study 1 are shown in Figure 4.



(**a**) (**b**)

Figure 6. Bioethanol supply chain in Case Study 2. (**a**) Selected biomass supplier; (**b**) customer regions supplied by biorefineries.

4.3. Discussion of the Relationship between Economic and Social Benefits

Both economic and social benefits are considered in the discussion. The ε-constraint method is employed to obtain a set of Pareto-optimal solutions to show the tradeoff between two objectives, as has been used in prior studies [6,7,37]. The procedure of the method is presented as follows.

Step 1. Solve the model with objective Equation (27) and constraint (14)–(25), find the value of the social benefits and let the value be the minimum value of the social benefits.

$$\max\ (AverageRevenue - AverageCost) + \lambda\left(SocialBenefits^{TotalWages} + SocialBenefits^{PurBM}\right), \tag{27}$$

where λ is a very small number (on the order of 10^{-6}).

Step 2. Solve the model with the social objective Equation (11), constraints (14)–(25) and (28):

$$AverageRevenue - AverageCost \geq 0, \tag{28}$$

which requires the revenue to be greater than the total cost. Let the value of the social benefits be the maximum value of the social benefits.

Step 3. Let $Interval = (MaximumValue - MinimumValue)/20$ and $p = 1$.

Step 4. Let $\varepsilon = MinimumValue + Interval \cdot p$, and solve the model with the objective function (27), constraints (14)–(25) and constraint (29):

$$SocialBenefits^{TotalWages} + SocialBenefits^{PurBM} \geq \varepsilon, \tag{29}$$

Step 5. If $p < 19$, $p = p + 1$, repeat *Step* 4; otherwise the method ends.

With the method, a set of Pareto-optimal solutions is obtained and the corresponding curve is shown in Figure 7. All solutions are arranged in increasing order of social benefits. The slope s_q ($2 \leq q \leq 20$) between adjacent solutions is calculated by:

$$s_q = \left(Economic_{q-1} - Economic_q\right)/\left(Social_q - Social_{q-1}\right), \tag{30}$$

where $Social_q$ and $Economic_q$ denote the social and economic benefits of solution q in the Pareto set. s_q means the ratio between the decrement of economic benefits and the increment of social benefits of adjacent solutions. The accumulative slope as_q between solution q and solution 1 is calculated as:

$$as_q = \left(Economic_1 - Economic_q\right)/\left(Social_q - Social_1\right), \tag{31}$$

where as_q ($2 \leq q \leq 20$) represents the ratio between the decrement of economic benefits and the increment of social benefits of solution q compared to solution 1. For decision makers, as_q shows the ratio between the loss of economic profits and the gain of social benefits of different supply chains compared to the supply chain with the maximum economic benefits. Both s_q and as_q are shown in Figure 7. It can be seen that as_q is smaller than 0.5 in a wide range.

There are nine different configurations of biorefineries and collection stations corresponding to the Pareto-optimal solutions, which are presented in Table 2 in increasing order of social benefits. It can be observed that with the social benefits increasing, facilities tend to be located in less-developed regions that have greater weights. Because less-developed regions are relatively far away from regions with greater demand, the total transportation cost increases with the increase in the social benefits. More facilities bring higher annualized construction costs.

As shown in Figure 7, at the left end of the social-economic curve, the slope is rather small, which means that the bioethanol supply chain could bring about social benefits with a small loss in profit.

The curves are also helpful for governments. In China, the government spends lots of money on guaranteeing basic living conditions for poor people and developing poor regions every year. The development of the bioethanol industry offers a better way to spend the money. Subsidizing bioenergy enterprises may bring about more social benefits than the subsidy spent. If a decision maker from an enterprise is unwilling to lose any profit to gain social benefits, it may be an option for governments to subsidize the enterprise to compensate for its economic loss so that the enterprise offers several times more social benefits than the subsidy through the bioethanol supply chain. The curve of as_q helps governments decide how much the subsidy should be to arrive at an appropriate input-output ratio.

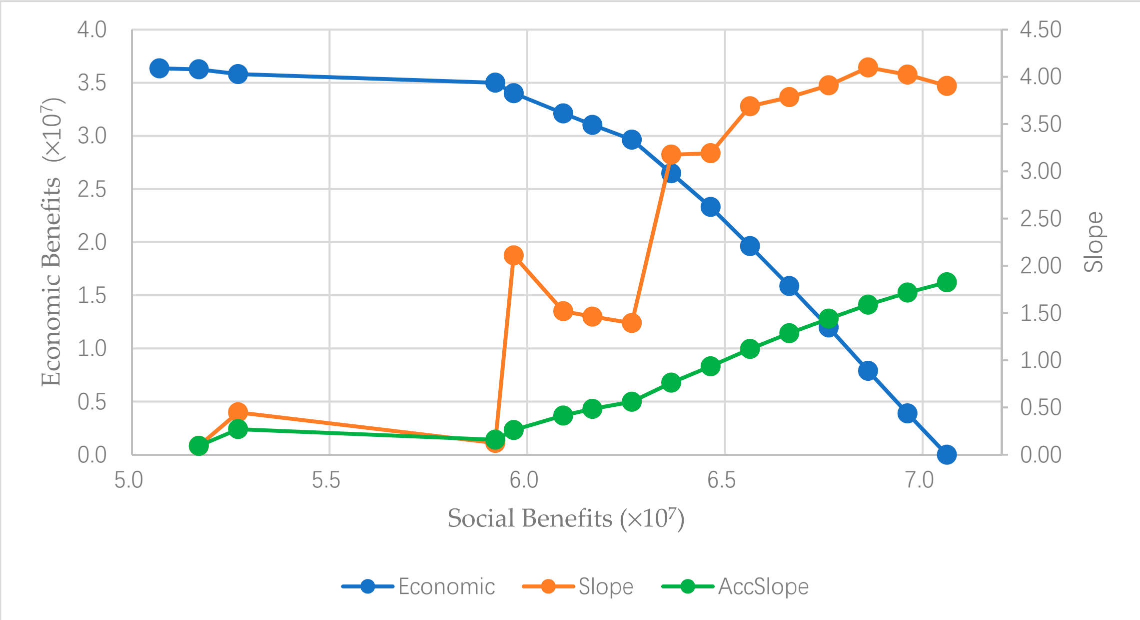


Figure 7. Pareto-optimal curve between economic and social benefits.

In our case, the value of s_2 is 0.09, which means social benefits equating to more than 10 times the subsidy can be offered through the bioethanol supply chain.

Table 2. Configurations of Pareto solutions.

Configuration	Biorefinery	Collection Station
1	Shenyang (1), Jinzhou (7)	Shenyang (1), Fushun (8), Jinzhou (7), Liaoyang (9), Panjin (3), Tieling (14), Huludao (10)
2	Shenyang (1), Jinzhou (7)	Shenyang (1), Fushun (8), Jinzhou (7), Panjin (3), Tieling (14), Huludao (10)
3	Shenyang (1), Jinzhou (7)	Shenyang (1), Jinzhou (7), Panjin (3), Tieling (14), Huludao (10)
4	Shenyang (1), Jinzhou (7)	Shenyang (1), Jinzhou (7), Chaoyang (13), Tieling (14), Huludao (10),
5	Anshan (5), Jinzhou (7), Tieling (14)	Anshan (5), Jinzhou (7), Tieling (14), Yingkou (4), Liaoyang (9), Huludao (10)
6	Anshan (5), Chaoyang (13), Tieling (14)	Anshan (5), Benxi (6), Jinzhou (7), Yingkou (4), Liaoyang (9), Huludao (10), Tieling (14)
7	Jinzhou (7), Tieling (14)	Panjin (3), Tieling (14), Chaoyang (13), Huludao (10)
8	Fuxin (12), Tieling (14), Chaoyang (13)	Jinzhou (7), Fuxin (12), Tieling (14), Chaoyang (13), Huludao (10)
9	Jinzhou (7), Tieling (14), Fuxin (12)	Jinzhou (7), Fuxin (12), Tieling (14), Chaoyang (13), Huludao (10)

Note: The number following the city name is the ranking of the city's per capita income in Liaoning Province.

5. Conclusions

Energy shortages, GHG emissions, and air pollution have been prompting the government to develop the bioethanol industry in China. It is necessary to research the optimal design of a bioethanol supply chain to assist enterprises and government with making decisions. China has a large number of people living in poverty. The bioethanol supply chain can offer many social benefits, which is a good opportunity for China to reduce poverty and increase the incomes of poor people. The main motivation for this study was to analyze the potential economic and social benefits of the bioethanol supply chain in Northeast China and determine the relationship between the two objectives.

A multi-objective MILP model was built to formulate the problem. A new method of measuring the social benefits was proposed. Two case studies in Liaoning Province analyzed the economic potentials of the bioethanol supply chain. In both cases, the bioethanol supply chain was proven to be profitable, with profit margins of 10.47% and 10.33%, respectively. The ε-constraint method was used to obtain the Pareto-optimal curve between economic and social benefits. The curve showed that the bioethanol supply chain could bring about many more social benefits with a relatively small loss of profit. In our case, the ratio between the loss in economic benefits and the gain of social benefits could be as small as 0.09. It was implied that governments may play an important role through subsiding enterprises so that enterprises can offer social benefits without economic losses.

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