Supply Chain Optimization of Forest Biomass Electricity and Bioethanol Coproduction

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Abstract

To establish a systematic and efficient forest bioenergy supply chain management system, most previous related studies did not investigate a system that involves generating two or more types of energy simultaneously, and did not consider the carbon emissions caused by electricity power generation of forest biomass combustion. Consequently, this study addressed the problems regarding the tactical supply chain optimization of a forest biomass electricity and second-generation bioethanol coproduction plant. A mixed-integer linear programming model was employed to determine the optimal production strategies to maximize the profit and to minimize the carbon emissions cost. The advantages of coproduction include enabling equipment and facility sharing, reducing investment costs, and dispersing the risks that involve raw materials, leading to synergy. Empirical simulation results indicated that the coproduction model yielded more profit than the independently operated model. When electricity demand is reduced, the coproduction model mitigates its profit losses through an increase in its bioethanol production. However, when faced with an increase in carbon emission costs, the coproduction model loses its advantages. According to the sensitivity analysis, electricity prices are the most vital parameter to the profit of the model, followed sequentially by the higher heating value of raw materials and carbon emission costs.

Keywords: Forest bioenergy, carbon emission, bioethanol, coproduction, supply chain optimization, mixed-integer linear programming

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Nomenclature

Notation

P	Set of types of raw materials (biomass) P = {Woodchips, Sawdust, Shavings, RLD}.	
δ_c	Set of the suppliers that have signed fixed contracts with the bioenergy coproduction plant $\delta_c = \{s_1, s_2, \ldots, s_m\}$.	
δ_u	Set of the suppliers that had not signed fixed contracts with the bioenergy coproduction plant $\delta_u = \{s_{m+1}, s_{m+2}, \ldots, s_n\}$.	
δ	Set of suppliers $\delta = \{s_1, s_2, \ldots, s_n\} = \delta_c \cup \delta_u$, where s_i is the ith supplier.	
T	Set of decision times in one year $T = \{Jan, Feb, \ldots, Dec\}$.	
p	$p \in P$	
s	$s \in \delta$	
t	$t \in T$	

Parameter

$AshC$	Average ash content of the raw materials.	%
$AshHC$	Unit cost of handling ash.	\$/green ton
$BC_{s,p}$	Unit cost of the raw material type p purchased from supplier s.	\$/green ton
$BCapacity$	Annual bioethanol capacity of the coproduction plant.	L
BD	Annual bioethanol demand in downstream markets.	L
BP_t	Unit bioethanol price in month t.	\$/L
CC	Carbon content, i.e., proportion of carbon in the raw material.	%
d_s	Distance between supplier s and the coproduction plant.	km
$efficiency$	Conversion efficiency for biomass electricity production.	%
$EV_{s,p,t}$	Energy value of the raw material p provided by the supplier s in month t.	MWh/green ton
$ECapacity$	Annual electricity capacity of the coproduction plant.	MWh
ED	Annual downstream electricity demand.	MWh
EP_t	Unit electricity price in month t.	\$/MWh
g	Unit quantity of carbon emitted from fossil-fuel-powered vehicles in raw material transportation.	Kg/ton-km
$HHV_{s,p,t}$	Higher heating value of the combustion of raw material p from supplier s in month t (energy estimation hypothesis) .	MWh/dry ton
$MaxF_{s,t}$	Maximal quantity of raw materials available from supplier s in month t.	green ton
$MaxS$	Raw material storage capacity limit of the coproduction plant.	green ton
$MC_{s,p,t}$	Proportion of water in raw material p provided by supplier s in month t.	%
$MFED_t$	Monthly firm electricity demand in month t.	MWh
$MFBD_t$	Monthly firm bioethanol demand in month t.	L
PCB	Unit bioethanol production cost (including water, chemical, and sewer costs).	\$/L
PCE	Unit electricity generation cost (including water, chemical, and sewer treatment).	\$/MWh
PSC	Penalty for violating the storage limit.	\$
QRF	Proportion of the decrease in raw materials' energy value when the storage falls below the lower storage limit (SLL).	%
$Ratio_{s,p,t}$	Proportion of raw material type p in all the raw materials provided by supplier s in month t.	%
r	Conversion rate of raw material to bioethanol.	L/green ton
SDL	Storage desired level (SDL) (i.e., exceeding this value leads to penalty).	green ton
SLL	Storage lower level (SLL) (i.e., falling below this value results in a decrease in the energy value of the raw material).	green ton
SUL	Storage upper limit; exceeding this value leads to penalty ($SUL > SDL$).	green ton
$TargetS$	Final target storage level.	green ton

TC	Unit raw material transportation cost.	\$/ton-km
β	Unit carbon emission cost.	\$/Kg
Decision variable		
$CB_{s,t}$	Quantity of the raw materials from supplier s consumed to generate bioethanol in month t.	green ton
$CE_{s,t}$	Quantity of the raw materials from supplier s consumed to generate electricity in month t.	green ton
$F_{s,t}$	Quantity of the raw materials purchased from supplier s in month t.	green ton
$S_{s,t}$	Quantity of the raw materials from supplier s stored in month t.	green ton
QB_t	Quantity of bioethanol generated in month t.	L
QE_t	Quantity of electricity generated in month t.	MWh
X_t	Binary variable: If the storage in month t exceeds SDL, then the variable equals 1; otherwise, the variable equals 0.	-
Y_t	Binary variable: If the storage in month t exceeds SUL, then the variable equals 1; otherwise, the variable equals 0.	-
Z_t	Binary variable: If the storage in month t falls below SLL, then the variable equals 1; otherwise, the variable equals 0.	-

1. Introduction

International Energy Agency (IEA) indicated that the global energy demand would be one-third higher than the 2015 energy demand by 2040 [1]. Because the current global energy supply structure is based on fossil fuels, such as petroleum, natural gas, and coal, the consumption of fossil fuels will increase to meet this demand, thereby exacerbating greenhouse gas emissions. To simultaneously meet the increasing energy demand, comply with the international regulations on greenhouse gas emissions, and limit the consumption of finite fossil fuel resources, the proportion of renewable energy in the global energy supply must expand from 13.5% to 30% by 2040 [1]. The importance of renewable energy has garnered attention worldwide, particularly bioenergy, which is promising as a source of renewable energy. For example, Mafakheri et al. [2] indicated that bioenergy is an attractive source of energy owing to various types of biomass resources and mature conversion technologies; and Rentizelas et al. [3] stated that biomass can be easily stored. Numerous studies have indicated that developing bioenergy will substantially facilitate the mitigation of climate change.

Forest biomass exhibits numerous advantages as the raw material for bioenergy, most notably its massive reserves. Currently, forests cover approximately 30% of the land on Earth and can be continuously regenerated, thus providing plentiful sources for biomass.

Furthermore, forest biomass can be stored for prolonged periods, and can be broadly applied. By contrast, fossil fuels have deviated from the carbon cycle for a prolonged period. Combusting fossil fuel increases the release of CO_2 into the atmosphere that has been fixed for billions of years, and exacerbates the global warming crisis. Therefore, replacing fossil fuels with forest biomass is a high potential and imperative solution for sustainable energy and environmental management [4].

The sources of biomass include woody, herbaceous, and aquatic plants, as well as manures [5], and can be categorized as primary, secondary, or tertiary biomass feedstock [6]. Unlike primary biomass (which is produced in natural or conservation areas), secondary and tertiary biomass are by-products or residues when processing primary feedstock or post-consumer residues and wastes. Note that this study only focused on secondary and tertiary biomass feedstock, and did not consider primary forest biomass as the energy feedstock in our modeling design. There are several ways to convert raw biomass feedstock into different final energy products (e.g., heat, power, biofuel, and biogas) [7]. According to the IEA [1], biofuel will constitute 27% of the global fuel market by 2050, confirming the trend of long-term biofuel development.

Recently, second-generation bioethanol production plants have emerged. Food crops have been replaced with forest biomass as raw materials, thereby eliminating controversy over the competition between bioethanol and humans for food. These second-generation bioethanol factories can effectively solve energy efficiency problems. Currently, bioethanol has contributed to the global bioenergy supplies the most substantially. Bioethanol plants can now be integrated with combined heat and power facilities for coproduction through the use of existing technology [8], thus leading to synergy and improved plant efficiency. When cellulosic ethanol production facilities are coconstructed with electricity power-generating facilities, not only can raw materials be shared between electricity power generation and ethanol production, but facilities can also be shared, thereby saving investment costs. Additionally, the waste heat generated from thermal electricity generation can be used for producing cellulosic ethanol [9]. These energy plant designs can lower the costs of energy production, raise its efficiency, dissipate its risks, and mitigate the high costs and uncertainties of forest biomass. Therefore, how decision makers adjust the proportions of bioethanol and electricity generation becomes crucial.

This study established the first model on the supply chain management (SCM) of a forest biomass electricity and second-generation bioethanol coproduction plant to solve the problems involved in the supply chain of the plants that coproduce two or more types of bioenergy, as well as the carbon emissions caused by forest biomass combustion. A mathematical model was formulated for simulation and scenario analyses on the coproduction of forest biomass electricity and second-generation bioethanol, to determine the optimal SCM approach.

A recently emerging second-generation bioethanol plant was integrated in an existing forest biomass power plant for coproduction. Although coproduction is achievable with the existing technology, no cases of mass production have been performed. Additionally, no studies have been conducted on the problems involved in the SCM of bioenergy plants. Therefore, this study explored the problems facing the SCM when a biomass electricity and bioethanol coproduction plant has achieved commercial-scale mass-production. On the most vital advantages of biomass electricity and bioethanol coproduction, in the face of fluctuating market prices, the proportion of bioethanol and biomass electricity production can be adjusted to maintain profit stability among coproduction plants and to lower the associated risks. Moreover, the coproduction of two products is more efficient, less energy-consuming, and costs less than independent bioethanol or biomass electricity generation. To verify that bioenergy coproduction lowers the associated risks more substantially than independent production, a bioenergy coproduction supply chain model was created, based on the supply chain model of a forest biomass power plant in [10] and modified according to the biofuel supply chain model of [11]. Scenario and sensitivity analyses were then conducted to examine the effects of bioethanol and electricity prices on the decisions in SCM and determine whether the coproduction model could lower the associated risks more considerably than independent production.

The contributions of this study are listed as follows:

- This study is the first to establish a mathematical programming model for the supply chain optimization of a forest biomass electricity and second-generation bioethanol coproduction plant, in consideration of the carbon emissions caused by forest biomass combustion.

- A comprehensive simulation analysis on the forest bioenergy coproduction model is conducted to check whether coproduction lowers more risks of lacking raw materials than independently operated bioethanol and biomass electricity production models.
- A sensitivity analysis is conducted to explore the effects of the forest bioenergy parameter changes on the profit of bioenergy supplies, thereby identifying the most critical factors that affect the forest bioenergy supply chain.
- A scenario analysis is conducted to explore the effects of the changes in carbon emission costs on the proportions of forest bioenergy production. In addition, this study investigates the proportional changes in production that accompany forest bioenergy coproduction in various scenarios, such as the changes in raw material supplies, the limitations on electricity demand (risk dissipation), and the rise in carbon emission costs.

The rest of this study is organized as follows. Section 2 gives the literature review. Section 3 describes the problem concerned in this study, and then establishes an MILP for this problem. Section 4 shows the simulation results, and gives sensitivity, scenario analyses, and detailed discussion on experiment results. Section 5 concludes this study.

2. Literature Review

This section first gives the introduction, categorization, and applications of bioenergy SCM. Then the previous works on supply chains of forest biomass power plants and biofuel are reviewed, respectively.

2.1. System framework for bioenergy supply chains

A supply chain is a complex network of suppliers, manufacturers, distributors, and markets connected by logistics and information flow [25], and SCM refers to the management and formulation of the decisions pertaining to supply chains [26]. These decisions range from investing and expanding plants to scheduling daily plant production. The concept of SCM was applied in various bioenergy plants, and an optimized SCM model was created. Finally, through the input of various parameters and model calculations, a set of optimal decisions were generated to provide decision makers with a reference for SCM; this was the bioenergy SCM problem focused on in this study.

Two methods were employed to categorize bioenergy SCM [27]. The first method involved dividing SCM into strategic, tactical, and operational levels according to its decision levels. The operational supply chain planning refers to short-term (e.g., weekly, daily, hourly) production decisions, such as the weekly amount of power converted in a plant, the daily number of working hours, and the daily number of raw materials to transport. The tactical supply chain planning involves medium-term (e.g., monthly) decisions, such as the monthly inventory and logistics management of a bioenergy plant. Finally, strategic supply chain planning involves long-term (e.g., yearly) decisions, such as the signing of contracts with specific suppliers and the locations to set up factories and distribution centers.

The second categorization method involved dividing SCM into upstream, midstream, and downstream decision-making according to the operational procedures of bioenergy supply chains. Upstream decisions consider the operations of producing, harvesting, and transporting raw materials from the starting point of the supply chain to a bioenergy plant. Midstream decisions reflect the operations of converting raw materials to energy products, varying according to each type of bioenergy plant. Finally, downstream decisions reflect the operations of inventorying energy products and distributing them to market services.

Most previous studies have employed various optimization models to process different types of bioenergy SCM and focused on various SCM categories. According to the aforementioned categorization methods, the bioenergy SCM studies were organized as shown in Table 1. The most relevant previous studies to this study were those conducted by [10] and [18]. However, no studies have employed an optimization model to examine the biomass electricity and bioethanol coproduction supply chain. Therefore, this study referred to the two aforementioned studies for the basic mathematical models to construct a novel model for this study.

Table 1. Classification of previous studies

Level	Operations	System	Objective	Model	Reference
Tactical	Upstream and midstream	Forest biomass power plant	Maximizing profit	MINP	[10]
Tactical	Upstream and midstream	Forest biomass power plant	Maximizing profit and minimizing risks	MILP and stochastic models	[16]
Tactical and strategic	Upstream and midstream	LIHD biomass to anaerobic digester	Maximizing energy output	MILP	[20]
Tactical and strategic	upstream	Forest biomass biofuel plant	Minimizing costs	MILP	[18]

2.2. Supply chain of forest biomass power plants

The intensive development of forest bioenergy has encountered numerous obstacles [12], such as insufficient conversion rates (e.g., raw materials contain high amounts of water and low amounts of thermal energy) [13], unstable raw material supplies (caused by climate and seasonal factors), high transportation costs (caused by geographical conditions and low raw material densities) [14], high processing costs, unstable raw material quality, and other uncertainties (e.g., policies, market conditions). Consequently, the system efficiency and resource usage rate of forest bioenergy have not met a comparable standard to that of other types of energy. Studies have reported that systematic and efficient SCM is required to solve the aforementioned problems [15].

Previous studies on SCM for bioenergy have focused on various fields such as the supply chains of wood biomass power plants, and biofuel plant supply chains. All of these studies have adopted mathematical programming models to characterize the supply chains. For example, Shabani and Sowlati [10] employed a mixed-integer nonlinear programming (MINP) model to solve the tactical supply chain problems of wood biomass power plants so as to maximize their profit. Shabani et al. [16] later extended the model in [10] into a stochastic programming model to deal with supply uncertainty. Frombo et al. [17] used a non-linear mixed integer programming model to find the optimal decisions that take into account all issues and costs/benefits related to the forest biomass use, transport and energy production. Zhang et al. [18] used a general mixed-integer linear programming (MILP) model to solve the facility location problem for biofuel plants with objective of minimizing their costs. The model involves considering the carbon footprint generated from raw material transportation and including costs to assess the quality of

SCM decisions. Azadeh et al. [19] proposed a stochastic programming model for the optimization of biofuel supply chains. Notably, Shabani and Sowlati [10] and Shabani et al. [16] only considered the actual costs of wood biomass power plants.

Because most of the studies of this type have focused on specific raw materials and products, De Meyer et al. [20] designed a general biomass-based supply chain model named OPTIMASS to simultaneously solve the strategic and tactical problems on upstream, midstream, and downstream bioenergy SCM decision-making. The OPTIMASS could be used in any type of bioenergy plants and might involve one of four objectives, namely profit maximization, net energy output maximization, job opportunity maximization, and global warming minimization. However, the OPTIMASS cannot simultaneously solve multiple objectives that conflict and trade off with one another; furthermore, most previous studies have focused solely on factories with a single output (e.g., biomass power plants, bioethanol plants, and biogas plants). Although De Meyer et al. [20] simultaneously explored biogas and compost output, compost was regarded as a byproduct, and its output was not considered in the objective equation. Therefore, only one type of output was actually considered in that study.

Few studies have addressed the costs of carbon emissions, and those that have addressed the problem have overlooked the carbon emission from energy conversion processes. According to the European Emissions Trading Scheme, bioenergy industries in the carbon trading market system [21] derived from the Kyoto Protocol are special industries, and the carbon emissions caused by forest biomass combustion is not included in the total amount of carbon emitted by a bioenergy-producing country. However, because combusting forest biomass still produces carbon emissions, bioenergy development has been questioned and inhibited. However, the doubt against bioenergy development could be mitigated if specific methods could be developed to solve the carbon emission problem caused by forest biomass combustion. The recently matured carbon capture and sequestration method may effectively solve this problem [22]. Additionally, the cost-effectiveness of bioenergy plants relative to other types of energy plants defines the quality of the bioenergy plants [23]. Nevertheless, the carbon emissions caused by forest biomass combustion are regarded as environmental costs [24];

recognition of this problem was included in the objective function of the model devised in the present study.

Shabani and Sowlati [10] investigated the supply chain of a forest biomass power plant in Canada, which was divided into multiple suppliers, transportation, raw material inventory, the plant itself, and the total market demand to determine the tactical value chain of such plants. The primary raw materials of the plant are the sawdust from local sawmills and other types of forest residue such as bark, shavings, and roadside logging debris (RLD), most of which are the byproducts of the local forest. The plant signs long-term or short-term contracts with nearby forestry owners, who become suppliers. The raw materials are then transported to the plant by the suppliers for storage. Subsequently, the plant determines the number of raw materials it must expend in a month to generate sufficient power to satisfy the monthly needs of its customers. In this case study, the production procedures of the plant are similar to those of a conventional power plant, in which raw materials are transported to boilers for combustion to produce water steam and conduct turbine power generation, thereby producing thermal and electric power as well as ash. However, this plant also differs from conventional power plants because its raw materials are forest biomass rather than coal.

To improve the efficiency of the supply chain of this plant, Shabani and Sowlati [10] developed an MINP model that aimed to maximize the profit of the plant and process the problems involved in upstream and midstream tactical decision-making. The decision variables involved were medium-term (i.e., monthly) decisions, including the number of raw materials purchased from a supplier, the number of raw materials stored, the number of raw materials consumed, and the amount of power produced (watt-hours, Wh).

2.3. Biofuel supply chain

Zhang et al. [18] conducted a case study on the forest biofuel plants in Michigan's Lower Peninsula. The supply chain of these biofuel plants comprises multiple locations for raw material production; raw material harvest, transportation, and storage; and plants. Notably, the Lower Peninsula has abundant forest resources, with a growth rate approximately twice that of the harvest rate; thus, the usage capacity in the area is considerable. However, using the forest resources requires certain costs. First, these resources are under three types of ownership, namely federal, state, and private ownership. Harvesting fees must be paid to forest owners, and the process of harvesting forest biomass also requires monetary costs. After raw materials are harvested from different woodlands, they are transported to various biofuel plants by trailer for production. Biofuel can be produced in solid (e.g., woods), liquid (e.g., ethanol), or gas (e.g., biogas) forms, but it commonly refers to bioethanol or biodiesel according to [28]. For example, Kralova and Sjöblom [29] discussed biodiesel as a biofuel. Naik et al. [30] discussed first and second generation biofuels, including biodiesel, bioethanol, alcohols, and bio-oil. Zhang et al. [18] did not specify the types of biofuel produced by the plants in their study, but the model descriptions suggested that the biofuel was liquid.

To calculate the possible locations of the plants, Zhang et al. [18] entered the geographic and statistical data of the Lower Peninsula into a geographic information system. The locations of the plants, production capacities, and annual transportation distances were then designated as the decision variables of the optimization model. The objective of the model was to minimize the costs of the biofuel plants. After the locations of the plants and their production capacities were determined, simulation software was employed to simulate the changes in daily inventory and the final costs in the supply chain network; the results were then fed back to the optimization model multiple times for parameter adjustment. Specifically, the simulation targeted the strategic and tactical planning problems in the upstream supply chain. Notably, the amount of carbon emitted from the facilities used for harvesting and transporting raw materials was included as part of the environmental costs in the cost calculation process of the model [24], which had not been considered in preceding biofuel supply chain studies. However, the carbon directly emitted in the plant production processes was still not considered.

3. Methods

An MILP optimization model for the problem of concern in this study is formulated in this section. Subsection 3.1 presents the problem. Subsection 3.2 explains the variables and symbols in the model as well as the hypotheses that guide this study. Subsection 3.3 presents the objective and constraint equations as well as highlights the differences between the model in the present study and those in previous studies.

3.1. Tactical supply chain of forest biomass power and second-generation bioethanol coproduction plants

The mathematical model developed in this study is based on the model in [16], in which this study further extends it with the amount of bioethanol output and carbon emission costs to satisfy the problem settings. This model considers dividing the planning time within a year into 12 months, in each of which a set of corresponding optimal management decisions are generated.

Although the supply chain as simulated in this study does not actually exist currently, it can be realized through the use of the contemporary technology. Therefore, this study creates a new optimization model to analyze the tactical supply chain of a forest biomass electricity and second-generation bioethanol coproduction plant. Based on the model on the forest biomass power plant supply chain in [10], this study additionally considers second-generation bioethanol production facilities in a power plant to enable the midstream coproduction of biomass electricity and bioethanol without changing the upstream operations. Thus, the supply chain comprises suppliers, transportation, raw material storage, biomass electricity and bioethanol coproduction, and total market demand (Fig. 1).

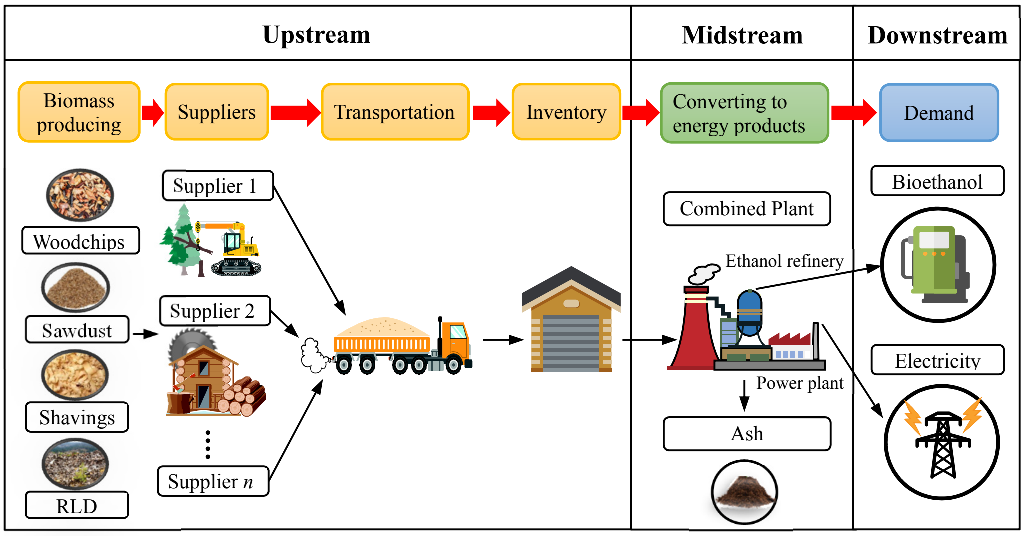


Fig. 1. Framework of the supply chain of forest biomass electricity and second-generation bioethanol coproduction.

The raw materials (identified as woodchips, sawdust, shavings, and RLD) are collected by the suppliers and purchased in varying numbers by the coproduction plant from a different supplier each month. Note that this study replaces bark from raw material in [10] by woodchips, because bark cannot be processed to bioethanol due to lack of lignocellulose (cellulose, hemicellulose, and lignin). In addition, this study assumes that the raw materials are mixed by the suppliers to make the conversion process stable. The materials are then transported to the plant for storage. Sufficient power and bioethanol are produced according to the monthly production plans to satisfy the downstream market demand, and generated through the turbine activities induced by the water steam from forest biomass combustion, which yields heat, electricity, and ash. Processing the ash in particular requires substantial monetary costs. The bioethanol is produced through two procedures [30], namely saccharification, in which the cellulosic raw materials are hydrolyzed into fermentable saccharides, and fermentation, in which the saccharides are converted to ethanol. The remaining lignin can be used as the solid fuel for power generation and provide the energy required for ethanol purification.

The tactical monthly decisional items in the upstream and midstream supply chain examined in the present study are listed as follows:

- The quantity of raw materials (biomass) purchase from a specific supplier;
- The quantity of raw materials stored;
- The quantity of raw materials consumed;
- The amount of power generated (Wh);
- The amount of bioethanol in kiloliters. Note that this item is new.

Our goal is to maximize the profit of the coproduction plant. Thus, unlike previous studies, this study includes bioethanol sales and the environmental costs of carbon emissions from forest biomass combustion in the profit calculation.

3.2. Assumptions and notations

The sets and indices used in the optimization model are presented in the "Nomenclature" section. Specifically, p is the type of raw material (out of woodchips, sawdust, shavings, and RLD), s is a supplier (out of a total of n, Suppliers $1 - m$ have signed fixed contracts with the bioenergy coproduction plant, and Suppliers $(m + 1)–n$ have not), and t is the decision time for the supply chain in each month of a year.

The parameters of the model are the constant values created according to the environment during modeling, in which in addition to those from [16], this study additionally considers the bioethanol output and costs of carbon emission during the production process.

The differences of this model from the model in [16] are summarized as follows:

- Firm demand (*FD*) and surplus demand (*SD*) in [16] are replaced with electricity demand (*ED*) and bioethanol demand (*BD*).
- Firm demand prices (*FP*) and surplus demand prices (*SP*) in [16] are replaced with electricity demand prices (*EP*) and bioethanol demand prices (*BP*).
- The monthly working hour parameter (WH_t) in [16] are removed because it would prevent the changes in the proportion of electricity and bioethanol production from being observed.
- To calculate the quantity of raw materials required for producing bioethanol, the conversion rate of raw materials to bioethanol (r) from the model employed by [18] is incorporated in the model of this study.
- The notation of the unit production cost of electricity is changed from *PC* to *PCE*, and the production cost of bioethanol (*PCB*) is implemented in the model.
- The parameters β, g, d_s, and *CC* (carbon content) are implemented to calculate the carbon emissions caused by fossil-fuel-powered trailers and forest biomass combustion.

The decision variables of the proposed model are also presented in the "Nomenclature" section, in which some variables are modified as follows:

- The quantity of raw materials from supplier s consumed in month t (C_{st}) is replaced with the quantity of raw materials from supplier s consumed for bioethanol production (CB_{st}) and electricity generation (CE_{st}) in month t.
- The amount of electricity generated in month t (E_t) is replaced with the amount of electricity (QB_t) and bioethanol ($QE_{s,t}$) generated in month t.

3.3. MILP model

The objectives and constraints, adjustments conducted on the proposed MILP model to solve the problems associated with bioethanol production, and hypotheses formulated in this study are described in this section.

This study maximizes the profit of bioenergy coproduction plants. Profit is calculated in several parts, and primarily involves the concept of revenue subtracted by cost. Herein, the costs are divided into procurement, ash handling, production, penalty storage, and carbon emission costs. Accordingly, the objective is expressed as follows:

$$\begin{aligned}\text{Maximize Profit} = &\text{ Revenue (2)} - \text{Procurement cost (3)}\\ &- \text{Ash hangling cost (4)} - \text{Production cost (5)}\\ &- \text{Penalty storage cost (6)} - \text{Carbon emission cost (7)}\end{aligned} \tag{1}$$

Notably, revenue is calculated as the sum of the earnings from bioethanol and electricity sales; in other words, the revenue is the sum of the annual amount of bioethanol produced × unit bioethanol price ($\sum_{t\in T}(QB_t \times BP_t)$) and the annual amount of electricity produced × unit electricity price ($\sum_{t\in T}(QE_t \times EP_t)$). Thus, revenue is calculated as follows:

$$\text{Revenue} = \sum_{t\in T}(QB_t \times BP_t) + \sum_{t\in T}(QE_t \times EP_t). \tag{2}$$

The raw material procurement costs are divided into purchase and transportation costs. The purchase cost is calculated as the total quantity of raw material p purchased from supplier s in month t ($F_{s,t} \times Ratio_{s,p,t}$) × the price of each tonne of the material ($BC_{s,p}$). The transportation cost is calculated as the total quantity of raw material p purchased from supplier s in month t × the distance between s and the plant × the transportation cost for each tonne–kilometer ($F_{s,t}$ × d_s × TC). Overall, the raw material procurement cost is calculated as follows:

$$\text{Procurement cost} = \sum_{s\in\delta, t\in T}\left[F_{s,t}\times\left(\sum_{p\in P}\left(BC_{s,p}\times Ratio_{s,p,t}\right)+d_s\times TC\right)\right]. \tag{3}$$

The ash handling cost is the unit ash handling cost ($AshHC$) × average ash content ratio ($AshC$) × the quantity of the raw material from the supplier s consumed for generating electricity in the month t ($\sum_{s\in\delta} CE_{s,t}$) as shown in the following:

$$\text{Ash hangling cost} = \sum_{t\in T}\left(AshHC\times AshC\times\sum_{s\in\delta} CE_{s,t}\right). \tag{4}$$

The production cost is the amount of electricity generated in t (QB_t) × the production cost of electricity (PCE) + the amount of bioethanol generated in t ($QE_{s,t}$) × the production cost of bioethanol (PCB), as shown in the following:

$$\text{Production cost} = \sum_{t\in T}\left(QB_t\times PCB+QE_t\times PCE\right). \tag{5}$$

The penalty storage cost is the penalty caused by the storage quantity exceeding the storage desired (SDL) or upper (SUL) levels. Because excessive storage requires the use of additional facilities and employees to process, which lowers the work efficiency of the plant, a penalty must be issued. The penalty storage cost is calculated as follows:

$$\text{Penalty storage cost} = \sum_{t\in T} PSC\times\left(X_t+Y_t\right). \tag{6}$$

The carbon emissions cost, the environmental cost newly added in the present study, is divided into two types. For raw material transportation, the cost of carbon emissions is calculated as the quantity of the raw material purchased from s in t ($F_{s,t}$) × the transportation distance between s and the plant (d_s) × the cost of each tonne–kilometer of carbon emissions (g × β). The carbon emissions caused by forest biomass combustion for electricity generation is calculated as the tonnes of raw materials from s combusted for generating electricity in t ($CE_{s,t}$) × the carbon content in each tonne of forest biomass (CC)

× the cost of each unit of carbon emitted (β). Overall, the carbon emission cost is calculated as follows:

$$\text{Carbon emission cost} = \sum_{s\in\delta,t\in T} F_{s,t}\times d_s\times\left(g\times\beta\right)+\sum_{s\in\delta,t\in T}\left(CE_{s,t}\times CC\right)\times\beta\times 1000. \tag{7}$$

The process of producing bioethanol is assumed to not emit carbon, unlike the process of generating electricity. This hypothesis leads to the trade-off between increasing the electricity capacity and reducing the carbon emissions cost, and causes an increase in the profit from bioethanol production. The effect of the interaction among the carbon emissions cost and electricity and bioethanol sales on their proportional production is one of the primary focuses in this study, which are examined in the follow-up sensitivity analysis.

3.3.1. Constraints

Eqs. (8)–(27) illustrate the constraints in the optimization model. Specifically, Eqs. (8)–(18) represent the constraints for raw material storage management, Eqs. (19)–(26) represent the constraints for the amounts of bioethanol and electricity produced, and Eq. (27) is the nonnegativity constraint of the decision variables. These equations are described in further detailed in this subsection.

First, the quantity limits in the raw materials purchased from a supplier are divided into two types. The suppliers that have signed fixed contracts with the coproduction plant ($s \in \delta_c$) define the quantity of raw materials that they need to provide in month t in advance, and the plant must procure all the raw materials from these suppliers; this is expressed in Eq. (8). By contrast, the suppliers that do not have signed fixed contracts with the coproduction plant ($s \in \delta_u$) provide the maximal quantity of raw materials equal to $MaxF_{s,t}$ in month t, and the plant can purchase a quantity lower than $MaxF_{s,t}$ from these suppliers; this is expressed in Eq. (9).

$$F_{s,t} = MaxF_{s,t}, \qquad \forall s \in \delta_c,\ t \in T; \tag{8}$$

$$F_{s,t} \le MaxF_{s,t}, \qquad \forall s \in \delta_u,\ t \in T. \tag{9}$$

Regarding storage limits, Eq. (6) indicates the penalty for exceeding the *SDL* and *SUL*, Eq. (10) represents the maximal storage capacity (*MaxS*), and Eq. (11) indicates the target storage standard that must be achieved by the end of a year *(TargetS*).

$$\sum_{s\in\delta} S_{s,t} \le MaxS\,, \qquad \forall t \in T; \tag{10}$$

$$\sum_{s\in\delta} S_{s,Dec} = TargetS\,. \tag{11}$$

Let *M* be a sufficiently large constant. Eqs. (12) and (13) are employed to set up the decision variable X_t for assessing whether the storage exceeds *SDL*. In other words, when the storage in month *t* is equal to or exceeds *SDL*, then $X_t = 1$; otherwise, $X_t = 0$.

$$\sum_{s\in\delta} S_{s,t} - SDL < M \times X_t\,, \qquad \forall t \in T; \tag{12}$$

$$\sum_{s\in\delta} S_{s,t} - SDL + M \times (1 - X_t) \ge 0\,, \qquad \forall t \in T. \tag{13}$$

Eqs. (14) and (15) are applied to set up the decision variable Y_t to assess whether the storage in month *t* exceeds *SUL*. In other words, when the storage exceeds *SUL*, $Y_t = 1$; otherwise, $Y_t = 0$.

$$\sum_{s\in\delta} S_{s,t} - SUL < M \times Y_t\,, \qquad \forall t \in T; \tag{14}$$

$$\sum_{s\in\delta} S_{s,t} - SUL + M \times (1 - Y_t) \ge 0\,, \qquad \forall t \in T. \tag{15}$$

Eqs. (16) and (17) are used to set up the decision variable Z_t, and assess whether the storage in month *t* falls below *SLL*. In other words, when the storage exceeds *SLL*, $Z_t = 1$; otherwise, $Z_t = 0$.

$$\sum_{s\in\delta} S_{s,t} - SLL < M \times (1 - Z_t)\,, \qquad \forall t \in T; \tag{16}$$

$$\sum_{s\in\delta} S_{s,t} - SLL + M \times Z_t \ge 0\,, \qquad \forall t \in T. \tag{17}$$

Eq. (18) is employed to calculate the storage volume of each supplier *s* at the end of month t ($S_{s,t}$). This is calculated as the final storage volume from the previous month ($S_{s,t-1}$) + the purchase volume of the present month ($F_{s,t}$) − the quantity of raw materials consumed for generating bioethanol ($CB_{s,t}$) and electricity ($CE_{s,t}$) in the present month.

$$S_{s,t} = S_{s,t-1} + F_{s,t} - CE_{s,t} - CB_{s,t}, \qquad \forall\, s \in \delta, t \in T. \tag{18}$$

Eqs. (19) and (20) represent the total annual production demand restrictions for bioethanol and electricity, respectively.

$$\sum_{t \in T} QB_t \le BD, \qquad \forall t \in T; \tag{19}$$

$$\sum_{t \in T} QE_t \le ED, \qquad \forall t \in T. \tag{20}$$

Eq. (21) is used to calculate the amount of bioethanol produced in month t (QB_t) through the multiplication of the quantity of raw materials provided by supplier s in month t by rate r of the conversion of the materials to bioethanol.

$$QB_t = \sum_{s \in \delta} CB_{s,t} \times r, \qquad \forall t \in T. \tag{21}$$

Eq. (22) is employed to calculate the amount of electricity produced in month t (QB_t). The variable is calculated as the quantity of raw materials from supplier s consumed in month t ($CE_{s,t}$) × the unit energy value of the raw material from s in t ($\sum_{p} \left(Ratio_{s,p,t} \times EV_{s,p,t} \right)$) × efficiency − the amount of decrease in the combustion energy caused by the storage volume falling below SLL (L_t).

$$QE_t = \sum_{s \in \delta} \left[CE_{s,t} \times \sum_{p \in P} \left(Ratio_{s,p,t} \times EV_{s,p,t} \right) \times efficiency \right] - L_t, \qquad \forall t \in T \tag{22}$$

where the unit energy value of the raw material type p from s in t ($EV_{s,p,t}$) is calculated as the higher heating value ($HHV_{s,p,t}$) and multiplied by the dehydration ratio ($1 - MC_{s,p,t}$), as shown in the following equation:

$$EV_{s,p,t} = HHV_{s,p,t} \times \left(1 - MC_{s,p,t} \right), \qquad \forall\, s \in \delta, p \in P, t \in T. \tag{23}$$

Eqs. (24)–(26) indicate the calculation methods for L_t. When raw materials are stored in a warehouse, their respiration increases their combustion energy value. However, the energy value of the materials decreases when their storage falls below its lower limit (*SLL*). Therefore, when L_t represents insufficient raw material storage (Z_t = 1), the energy value of the raw material combustion in month *t* must be multiplied by the quality decrease ratio *QRF*. This calculation process is divided into the following three equations for linearization [6]:

$$L_t \le M \times Z_t, \quad \forall t \in T; \tag{24}$$

$$L_t \le QRF \times \sum_{s \in \delta} \left[CE_{s,t} \times \sum_{p \in P} \left(Ratio_{s,p,t} \times EV_{s,p,t} \right) \times efficiency \right], \quad \forall t \in T; \tag{25}$$

$$L_t \ge QRF \times \sum_{s \in \delta} \left[CE_{s,t} \times \sum_{p \in P} \left(Ratio_{s,p,t} \times EV_{s,p,t} \right) \times efficiency \right] - M \times (1 - Z_t), \ \forall t \in T. \tag{26}$$

Moreover, the monthly upper limits of the coproduction plant in bioethanol and electricity production capacities must be considered when calculating the maximal bioethanol and electricity capacities in month *t*. As demonstrated in Eqs. (27) and (28), the quantities of bioethanol and electricity produced each month must not exceed their monthly maximal production capacities. In the present study, the maximal production capacity is assumed to remain consistent each month; thus, the annual production capacity is divided by 12 months for the monthly maximal production capacity.

$$QB_t \le BCapacity/12, \quad \forall t \in T; \tag{27}$$

$$QE_t \le ECapacity/12, \quad \forall t \in T. \tag{28}$$

Eqs. (29) and (30) reveal the minimal bioethanol and electricity capacities, which must be known alongside their maximal output. In consideration of the actual conditions, the production quantity in each coproduction plant must be maintained at its minimal fixed production capacity. The purpose of this calculation procedure is to satisfy the mandatory downstream bioethanol and electricity demands, namely the monthly fixed demands for bioethanol ($MFBD_t$) and electricity ($MFED_t$). Consumers may sign contracts with coproduction plants to ensure that the plants provide specified minimal amounts of bioethanol and electricity each month. The amounts of bioethanol and electricity produced may exceed the monthly fixed demands according to the conditions of the plants in certain months to fulfill the total annual production demand of the two energy products, outlined in Eqs. (19) and (20):

$$QB_t \geq MFBD_t, \qquad \forall t \in T; \tag{29}$$

$$QE_t \geq MFED_t, \qquad \forall t \in T. \tag{30}$$

Finally, the nonnegativity constraints for all the decision variables are listed as follows:

$$F_{s,t},\ S_{s,t},\ CB_{s,t},\ CE_{s,t},\ QB_t,\ QE_t \geq 0,\ \forall t \in T. \tag{31}$$

3.3.2. Differences between previous studies and the present study

The model employed in this study differs markedly from those of previous studies on the following characteristics:

1) The revenue structure is changed in this model to add the revenue from bioethanol sales.
2) The transportation cost (part of the procurement costs) is modified to vary according to the distance between the supplier and the plant.
3) The bioethanol production cost is included in the production costs in this model.
4) Carbon emission costs, a new category of environmental costs that includes the costs of the carbon emission caused by raw material transportation and plant production processes, are added.
5) The calculation of the monthly raw material storage in this model includes the consumption of the materials in bioethanol production.
6) The problems associated with the amount of bioethanol produced are considered.

7) The calculation of monthly electricity outputs vary according to the changes in the bioethanol prices and carbon emissions costs, rather than working hours in previous studies.

8) The monthly electricity and bioethanol prices vary, rather than previous studies assuming fixed electricity prices.

9) In addition to fulfilling the monthly firm demand, the coproduction plant in this study could decide whether to produce additional bioethanol and electricity according to their conditions in the specified months, and as long as the annual total production capacities are no higher than the annual total demand.

10) The monthly maximal production capacities are added and calculated by dividing the annual maximal production capacities by 12 months.

4. Experiment Procedures and Results

This section describes the goal and design of the experiment, explains the hypotheses and simulation conducted in this study, and presents the results of the experiment and scenario and sensitivity analyses.

This study employs the advanced integrated multidimensional modeling software (AIMMS) to construct a mathematical programming model for the coproduction problem in this study, and performs the simulation, scenario, and sensitivity analyses. First, this study verifies the capability of the coproduction model to lower the risks associated with the volatility in energy product prices, relative to that of the independently operated plant models. Next, this study examines the effect of the proportion of the environmental costs of carbon emissions to the total costs of the coproduction plants, and the effect of carbon emission costs on proportion of bioethanol and electricity production. Finally, some suggestions are provided to the decision makers of energy production plants for a reference.

For the remainder of this section, Subsection 4.1 describes the numerical values and references of the parameters (such as the unit carbon emission cost, which is an unchangeable parameter), the environmental parameters of the simulated plant (such as the number of suppliers and the quantities of raw materials they provide), the downstream annual electricity and bioethanol demand, and the storage capacity of the warehouse. Subsection 4.2 presents the optimized decisions and profit of the plant through a series of experimental results. Specifically, Subsection 4.3 explains the various situations simulated to verify the hypotheses, and Subsection 4.4 presents the sensitivity analysis results regarding the effects of the parameter changes on the profit of the plant. In addition, the effect of carbon emission costs on the proportion of bioethanol and electricity production is explored.

4.1. Experimental data and environment

The parameters in the model are divided into two types: real and simulated parameters. The values and references of the real parameters are listed in Table 2. Notably, no actual data on the simulated parameters are available; thus, the parameters are assumed to be uniformly distributed. A set of parameter values are randomly generated in a reasonable range; the range of values and references of these parameters are provided in Table 3. The primary parameters are based on the values acquired in the case studies by [10] and [18], and the remaining parameters are based on the open data from other studies or public agencies.

Table 2. Real parameters.

Parameter	Value	Reference
AshC	8 %	[10]
AshHC	0.58 $/green ton	[10]
CC	3.75 %	[31]
efficiency	30 %	[10]
g	0.119 Kg/ton-km	[32]
PCB	0.34 $/L	[33]
PCE	2.8 $/MWh	[10]
QRF	6 %	[10]
r	140 L/green ton	[33]
TC	0.051 $/ton-km	[18]
β	0.144 $/Kg	[18]

Table 3. Setting the simulated parameters.

Parameter	Value	Reference
$BC_{s,p}$	8.0~12.0 \$/green ton (with contracts) 10.0~30.0 \$/green ton (without contracts)	[34] (assumed to be uniformly distributed)
BCapacity	5,000,000 L	[35], [36]
BD	5,000,000 L	Assumed to equal the production capacity
$MFBD_t$	200,000 L	Assumed to be 4% of the annual demand
BP_t	0.35~0.65 \$/L	[37] (assumed to be uniformly distributed)
d_s	5.0~50.0 km (with contracts) 50.0~500.0 km (without contracts)	This study (assumed to be uniformly distributed)
$EV_{s,p,t}$	- (MWh/green ton)	Calculated through $HHV_{s,p,t}$ and $MC_{s,p,t}$
ECapacity	1,500,000 MWh	[38], [39]
ED	600,000 MWh	[10]
$MFED_t$	24,000 MWh	Assumed to be fixed at the 4% of *ED*
EP_t	49~91 \$/MWh	[40] Assumed to be uniformly distributed
$HHV_{s,p,t}$	3.68~5.34 MWh/dry ton	[10] (assumed to be uniformly distributed)
$MaxF_{s,t}$	0~14,177 green ton (with contracts) 0~20,800 green ton (without contracts)	[10] (assumed to be uniformly distributed)
MaxS	210,000 green ton	This study
$MC_{s,p,t}$	10.2 ~ 46.7 %	[10] (assumed to be uniformly distributed)
$Ratio_{s,p,t}$	0~100 %	Proportion randomly generated
SDL	15,000 green ton	This study
SLL	30,000 green ton	This study
SUL	180,000 green ton	[10]
TargetS	120,000 green ton	[10]

For our simulation, this study assumes a bioethanol and electricity coproduction plant to be located nearby Ontario and Quebec in Canada, with suppliers positioned 5–500 km away. The environmental parameters of this plant are based on the possible data values on the region to closely resemble its actual condition (Tables 5 and 6). The following hypotheses are established on the base case scenario:

- The annual downstream bioethanol demand (*BD*) equals the annual maximal bioethanol production capacity of the plant: Currently, because bioethanol is still being developed and few bioethanol plants have entered the mass-production stage, reliable data sources on the downstream bioethanol demand are lacking. Therefore, the demand for bioethanol is assumed to equal its production capacity. However, the total annual bioethanol demand in Canada is 5% of the gasoline demand (2.2 billion L), considerably higher than the maximal annual production capacity of the cellulosic ethanol demonstration plant, Enerkem, in Westbury, Quebec (5 million L).

- Downstream annual electricity demand (*ED*): This parameter is estimated according to [10]. The maximal production capacity of the plant is based on the data from a biomass power plant, Ontario Power Generation, in Thunder Bay, Ontario.

The aforementioned parameter settings and simulation data are entered into the AIMMS and calculated using CPLEX.

The proposed model is designed for a generalized optimization problem concerned in this study, and hence can be applied to any part of the world. In this section, the model is experimentally evaluated on a Canadian case, because the Canadian parameter values required in this model can be obtained from literatures. By just simply changing the parameter values used in the objectives and constraints, this model can be applied to simulate the problems for other parts of the world. For example, the value of parameter β (unit carbon emission cost; dollars to be paid for every kilogram of CO_2 emission) in Eq. (7) can be adjusted based on the policies of a certain country.

4.2. Experimental analysis

This subsection gives various experimental analysis results of the optimization model.

4.2.1. Analyzing the profit, revenues, and costs in the optimized results

To compare the optimizations results with and without coproduction, this study considers three cases as follows:

1) Case 1 (coproducing biomass electricity and bioethanol): Table 4 presents a list of the optimized profit, revenues, and costs of the coproduction model. This plant would generate annual revenue of approximately US\$48.92 million; specifically, electricity revenue would be approximately US\$46.71 million, and bioethanol revenue would be US\$2.20 million. The two revenues vary massively (by approximately US\$44.51 million) because of the difference between the bioethanol and electricity demand. The annual cost of the plant would be approximately US\$42.06 million, with carbon emission costs constituting the largest proportion (US\$29.49 million, 70.1%) followed by procurement costs (US\$9.11 million, 21.6%). Accounting for more than 90% of the total annual cost, these two prices

become the primary monetary expenses of the coproduction plant. Overall, the annual profit of this plant would be approximately US$6.85 million.

Table 4. Profit, revenues, and costs in the optimized results (unit: US$ million)

Item	Result
Profit	**6,859,552**
Revenue	**48,925,231**
-Revenue from selling bioethanol	2,206,121
-Revenue from selling electricity	46,719,110
Procurement Cost	**9,111,323**
-Purchase Cost	7,621,390
-Transportation Cost	1,489,933
Carbon Emission Cost	**29,498,593**
Production Cost	**3,159,000**
Ash Handling Cost	**296,763**
Storage Penalty Cost	**0**

2) Case 2 (producing only biomass electricity): Table 5 presents a list of the optimized profit, revenues, and costs of the independent biomass electricity power generation model (without bioethanol production), assuming that the prices and quantities of raw materials remain consistent. The annual bioethanol demand (*BD*) and monthly firm bioethanol demand ($MFBD_t$) are set to zero to simulate the optimal operation plan for an independently operated forest biomass power plant. The simulation results indicated that the plant would generate an annual revenue of US$46.74 million, which is US$0.03 million more than the electricity revenue results of the coproduction model. The total annual cost of this plant would be approximately US$40.21 million, with carbon emission costs again constituting the largest proportion (US$29.60 million, 73.6%) followed by procurement costs (US$8.63 million, 21.4%). Compared with the coproduction model, the total carbon emissions cost of the independent electricity generation model would be US$0.11 million higher. Overall, the annual profit of this plant would be approximately US$6.52 million, or US$0.33 million lower than the profit of the coproduction plant.

Table 5. Profit, revenues, and costs in the optimized results when only electricity is produced (unit: US$ million)

Item	Result
Profit	**6,525,792**
Revenue	**46,740,090**
-Revenue from selling bioethanol	0
-Revenue from selling electricity	46,740,090
Procurement Cost	**8,630,882**
-Purchase Cost	7,303,383
-Transportation Cost	1,327,499
Carbon Emission Cost	**29,605,006**
Production Cost	**1,680,000**
Ash Handling Cost	**298,410**
Storage Penalty Cost	**0**

3) Case 3 (producing only bioethanol): Table 6 presents a list of the optimized profit, revenues, and costs of the independent second-generation bioethanol production model (without electricity generation), assuming that the prices and quantities of raw materials remain consistent. The annual electricity demand (*ED*) and monthly firm electricity demand ($MFED_t$) are set to zero to simulate the optimal operation plan for an independently operated second-generation bioethanol plant. Notably, because the bioethanol demand is considerably lower than the electricity demand, this model's results could cause the over-purchasing of raw materials and the losses of the bioethanol plant; thus, two changes are required for the model to rationalize its simulation results. First, the Eq. (8) constraint, in which the bioethanol plant must purchase all the raw materials from its suppliers that have signed fixed contracts with the plant, must be relaxed; therefore, Eq. (8) is revised to $F_{s,t} \le MaxF_{s,t}$, $\forall s \in \delta_c$, $t \in T$. Second, the Eq. (11) constraint, in which storage of the bioethanol plant must reach the final target level, must also be relaxed; therefore, Eq. (11) is revised to $\sum_{s \in \delta} S_{s,Dec} \le TargetS$. These changes are performed to prevent undue losses at the plant caused by the over-purchasing of raw materials.

Table 6. Profit, revenues, and costs in the optimized results when only bioethanol is produced (unit: US$ million)

Item	Result
Profit	**412,176**
Revenue	**2,206,121**
-Revenue from selling bioethanol	2,206,121
-Revenue from selling electricity	0
Procurement Cost	**305,615**
-Purchase Cost	277,849
-Transportation Cost	27,766
Carbon Emission Cost	**9,330**
Production Cost	**1,479,000**
Ash Handling Cost	**0**
Storage Penalty Cost	**0**

The simulation results in Table 6 indicated that this plant would generate an annual revenue of US$2.20 million, which is nearly equal to that of the coproduction model. The total annual cost of this plant would be approximately US$1.79 million, and unlike the preceding two examples, the production costs would constitute the largest proportion of the total cost (US$1.47 million, 66.8%). Notably, compared with the coproduction model, the total carbon emission costs of the independent bioethanol production model would be US$29.48 million lower (only US$0.009 million); however, the procurement costs would still constitute the second highest proportion of the expenses (US$0.30 million, 16.7%). Overall, the annual profit of this plant would be approximately US$0.41 million, or US$6.44 million lower than that of the coproduction plant.

4.2.2. Analyzing the quantities of raw material procurement, storage, and consumption in the optimized result

Fig. 2 illustrates the optimized monthly quantities of raw material procurement, storage, and consumption in the coproduction plant. The total quantity of consumption (the purple line) exhibited irregular fluctuation, which is attributed to changing electricity prices. Specifically, electricity prices are higher than average in January, June, July, August, September, and November, and thus the profit from electricity production is particularly high; during these times, the quantity of production should increase within the production capacity of the model. If the minimal electricity demand is met, then electricity production would not be required in the remaining months; indeed, producing electricity in the months with insufficient pricing may even lead to business losses. Thus, the storage level continually increases before June, peaked in that month, is maintained at the desired level in July and August, and then sharply decreases in September when the electricity prices are at their annual high and electricity generation is sizable.

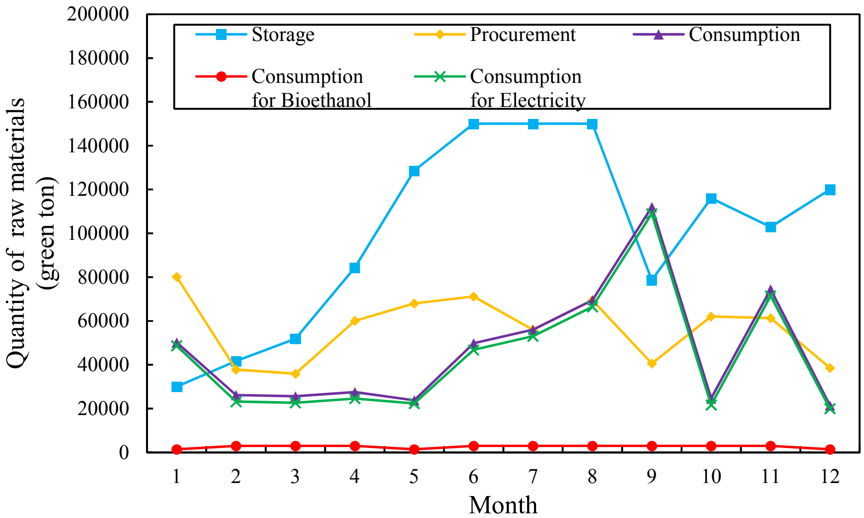


Fig. 2. Monthly quantities of raw material procurement, storage, and consumption in the optimized results.

From October to December, the storage level is slightly lower than the final target storage level, which indicates that the procurement strategies of the plant would be conducted in correspondence with changes in the electricity prices. During the months with low electricity prices, the storage level would be raised through procurement, thereby maintain a sufficient amount of raw materials for consumption during optimal production opportunities. Compared with the storage level and the quantity of consumption, the quantity of procurement is relatively stable, and thus would benefit the cooperation between the plant and its suppliers. Other factors that can affect the quantity of procurement (though to a lesser extent) include the quantity of raw materials provided by suppliers that have signed fixed contracts with the plant ($MaxF_{s,t}$), the price of raw materials, and the quality of raw materials ($EV_{s,t,p}$). Notably, because of the difference between the bioethanol and electricity demands, production plans have primarily focused on electricity, whereas bioethanol has been largely overlooked.

4.2.3. Analyzing the monthly electricity and bioethanol output in the optimized results

As depicted in Fig. 3, electricity output is relatively high in January, June, July, August, September, and November, when the prices are substantially high. Particularly, the maximal electricity output is observed in September, when the price is the highest. Similarly, bioethanol output is maximized for all the months excluding January, May, and June, when the bioethanol prices are relatively low. Moreover, the total bioethanol output does not attain the total annual demand, mainly because producing bioethanol in January, May, and June would lead to business losses; abandoning bioethanol production activities to meet the total annual demand is desirable during those months. Because of the sufficiency of raw material supplies, no resource competition is observed between bioethanol production and electricity production. However, in the months with low electricity output (February, March, April, and October), bioethanol production supplements the idle electricity production in the coproduction plant.

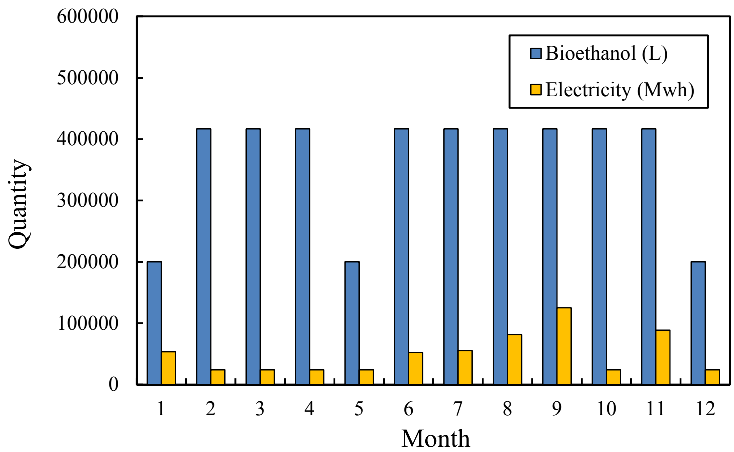


Fig. 3. Monthly electricity and bioethanol output in the optimized results.

4.2.4. Analyzing the carbon emission costs and their ratio in the optimization results

In the independently operated forest biomass power plant model, the total carbon emissions cost in our simulation is US$29.60 million, constituting a sizable 73.6% of the total cost of the plant. This implies that carbon emission costs will be the heaviest expense when the Canadian government begins taxing power plants on their carbon emissions. The Paris Agreement, which is signed by various countries including Canada, has increased the likelihood of this taxation. Conversely, in our simulation of the independently operated bioethanol plant model, the total carbon emissions cost is only US$0.009 million, or 0.5% of the total cost of the plant.

Currently, the total carbon emissions cost of the electricity and bioethanol coproduction model is estimated to be US$29.49 million, which constitutes 70.13% of its total cost (Fig. 4) and is 3.47% lower than that of the independently operated electricity production model. This confirmed the hypothesis that replacing part of the electricity production with bioethanol production would reduce the carbon emissions cost and its ratio. However, the reduction would be limited because of the insufficient bioethanol demand at present. Conversely, when bioethanol demand increases, the carbon emissions cost borne by the coproduction plant will profoundly decrease, and its overall profit will increase.

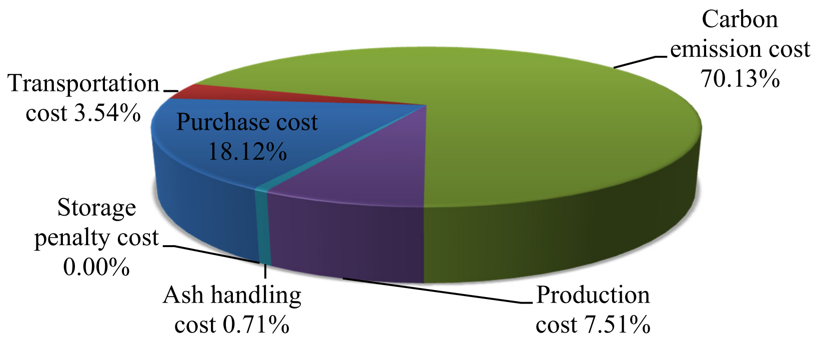


Fig. 4. Pie chart for all costs in the optimized result.

4.3. Scenario analysis

The results of the scenario analysis, which examine changes in the coproduction plant in various situations, are presented here. The maximal profit, revenue, and costs of the plant, as described in the preceding subsection, are regarded as the base case scenario and compared with the following three scenarios to verify the advantages of the plant in diverse settings.

1) Case1: Decrease in raw material supplies

In the result in the previous subsection, because of the sufficient raw material supplies, no resource competition is noted between bioethanol and electricity production. However, the supplies of forest biomass are not always overly abundant and may decrease in conjunction with the decline of local economies [10]. Therefore, this study considers the following case: With other environmental conditions remain unchanged, the suppliers without fixed contracts with the plant somehow stop providing raw materials. Consequently, the quantity of available raw materials decrease substantially and falls below the total quantity required for thoroughly satisfying the total annual electricity and bioethanol demand. In this condition, the coproduction plant would be required to reduce its electricity or bioethanol output; determining which product's output must be reduced and by how much is the focus of Case 1.

The simulation results reveal that both electricity and bioethanol outputs decrease in this case (Fig. 5). Specifically, the annual electricity output is reduced by approximately 30% (from 600,000 GWh to 420,000 GWh) and the annual bioethanol output is lowered by approximately 27.4% (from 4.35 million L to 3.28 million L). Consequently, the profit of the coproduction model would be lower than that of the independently operated power plant model, by approximately US$708.85 million (Table 7). This indicated that the coproduction model would lose all of its advantages when faced with raw material insufficiency. Moreover, the two independent models are equal in their procurement costs, which implies that when the quantity of raw materials remained the same but finite, some of the material otherwise used for generating electricity would be applied to produce bioethanol to satisfy the monthly firm bioethanol demand ($MFBD_t$). However, during the months when bioethanol prices are low, this tactic would not generate profit for the plant.

In other words, when raw materials are insufficient, bioethanol and electricity production would be forced to complete for resources during some months and the overall profit of the coproduction plant would be lower than that of the independently operated power plants.

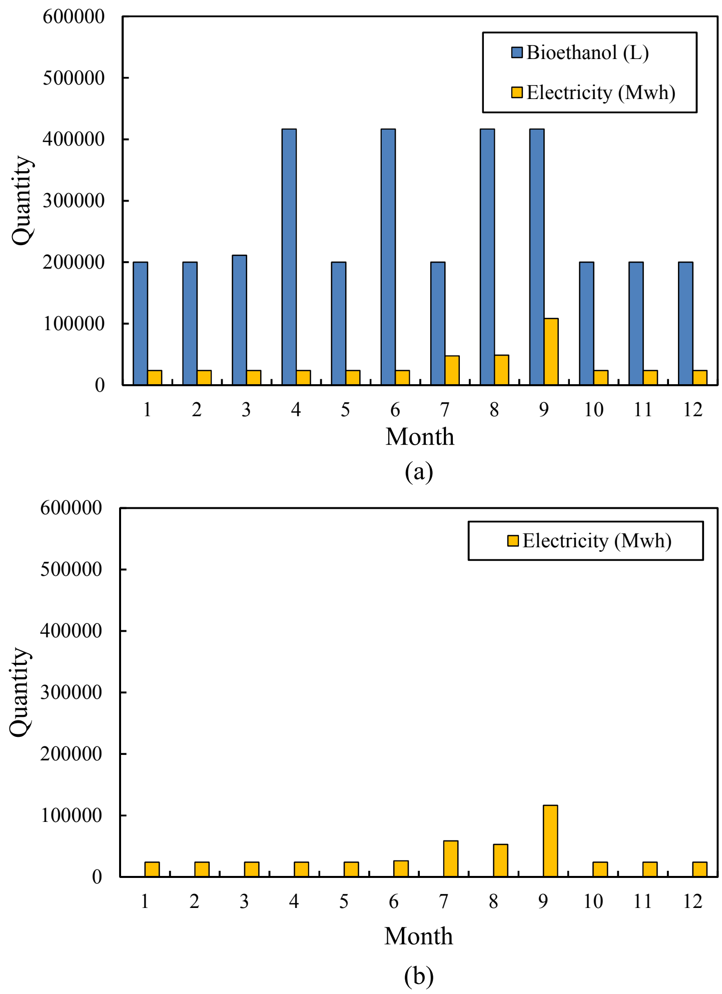


Fig. 5. Monthly electricity and bioethanol outputs in Case 1 for (a) the coproduction plant and (b) independently operated power plant.

Notably, the aforementioned results could change when the annual bioethanol production capacity (*BCapacity*) is twice as high as its original value. Fig. 6 shows the monthly electricity and bioethanol outputs in this condition. Table 8 presents a summary of the optimized profit of the coproduction plant in this condition, which is calculated to be US$6640 higher than that of the independently operated power plants. This is a substantial advantage that the coproduction plant exhibits in this condition; specifically, in the months with high bioethanol prices, the plant can produce higher quantities of bioethanol to expand their profit.

Table 7. Profit, revenues, and costs in the results of coproduction plant and independently operated power plant in Case 1 (unit: US$ million)

Item	Coproduction model	Power plant model
Profit	**4,146,188**	**4,217,073**
Revenue	**33,961,450**	**34,282,360**
-Revenue from selling bioethanol	1,686,532	0
-Revenue from selling electricity	32,274,918	34,282,360
Procurement Cost	**5,876,040**	**5,876,040**
-Purchase Cost	5,150,095	5,150,095
-Transportation Cost	725,945	725,945
Carbon Emission Cost	**21,428,965**	**22,710,199**
Production Cost	**2,293,451**	**1,249,130**
Ash Handling Cost	**216,806**	**229,918**

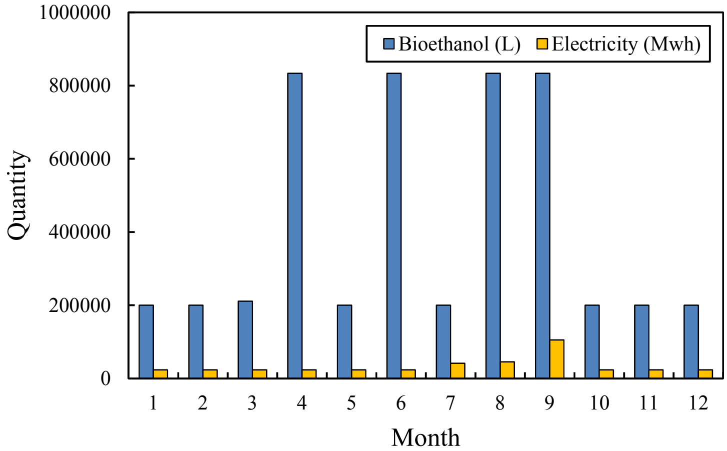


Fig. 6. Monthly electricity and bioethanol outputs when *BCapacity* is twice as high as its original value in Case 1.

Table 8. Profit, revenues, and costs in the results of coproduction plant and independently operated power plant when *BCapacity* is twice as high as its original value in Case 1 (unit: US$ million)

Item	Result
Profit	**4,223,713**
Revenue	**33,911,676**
-Revenue from selling bioethanol	2,659,491
-Revenue from selling electricity	31,252,185
Procurement Cost	**5,876,040**
-Purchase Cost	5,150,095
-Transportation Cost	725,945
Carbon Emission Cost	**20,777,536**
Production Cost	**2,824,247**
Ash Handling Cost	**210,140**

In summary, when the raw material supplies are reduced, the profit of the coproduction plant would not differ considerably from that of the independently operated plants.

2) Case 2: Decrease in electricity demand

Because of climate change, limited resources, advancing technology, and changing lifestyles, the types and quantities of energy in demand have changed considerably. In this scenario, the market electricity demand may drop by 20%; whether a coproduction plant could supplement the subsequent loss of profit from electricity production through bioethanol production is the focus of Case 2.

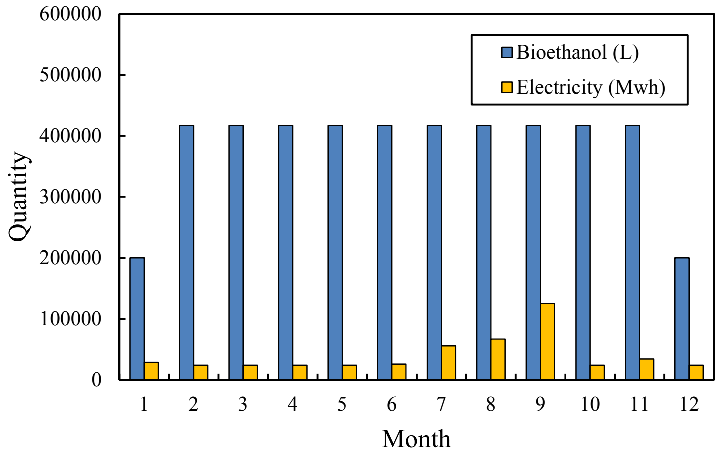
The simulation results indicate that the profit of the coproduction plant in this scenario is US$1.31 million lower than that of the base case scenario. Additionally, the annual bioethanol output increases from 4.35 million L to 4.57 million L, which suggests that the coproduction plant would supplement the loss caused by the decline in the electricity demand by increasing its bioethanol output. Furthermore, when the electricity demand is reduced, the profit of the coproduction plant is US$0.52 million higher than that of the independently operated power plant (Table 9), which reveals that the coproduction plant would exhibit a considerable advantage in this scenario because it is capable of producing bioethanol to meet other demands and generate profit.

Table 9. Profit, revenues, and costs in the optimized results of coproduction plant and independently operated power plant in Case 2 (unit: US$ million)

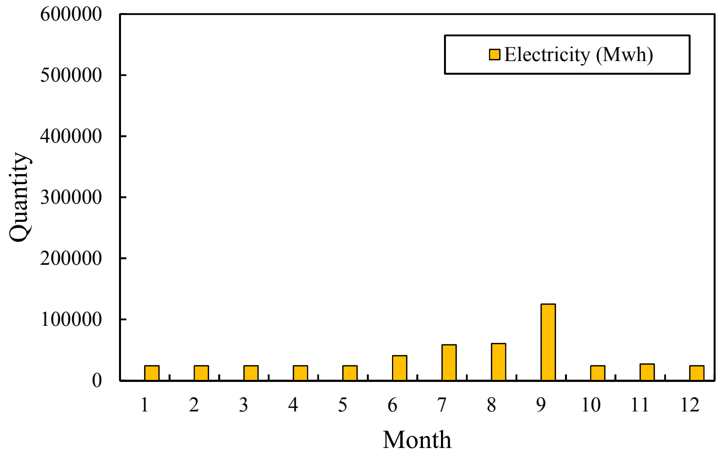
Item	Coproduction model	Power plant model
Profit	**5,541,834**	**5,015,717**
Revenue	**39,452,979**	**37,019,825**
-Revenue from selling bioethanol	2,289,611	0
-Revenue from selling electricity	37,163,368	37,019,825
Procurement Cost	**7,033,715**	**6,409,329**
-Purchase Cost	6,091,295	5,582,887
-Transportation Cost	942,420	826,441
Carbon Emission Cost	**23,741,040**	**24,007,924**
Production Cost	**2,896,667**	**1,344,000**
Ash Handling Cost	**239,723**	**242,853**

Fig. 7 shows that the output of biomass electricity power plant in June (Fig. 7(b)) is lower than that of coproduction plant (Fig. 7(a)). This result implies that when producing bioethanol is more profitable than producing electricity, coproduction plant will lower the output of electricity in order to produce bioethanol. The demonstration shows that bioethanol has the potential to replace a portion of electricity production and thus gives the coproduction plant flexibility to deal with the uncertainty from producing electricity.

As noted earlier, the bioethanol and electricity revenues vary substantially because of the difference in their demands. However, this case study explore the amount of increase that would be required in the bioethanol demand for the revenue to equal that of the forest biomass electricity as the energy market changes. The results in Fig. 8 and Table 10 indicate that the revenue of bioethanol power would be equal to that of electricity (approximately US$4.7 million) when the annual demand and production capacity of bioethanol reached 18 million L (3.6 times the current demand and capacity). Note that because this case has a significant increase output of bioethanol as compared to other cases, the unit of bioethanol in Fig. 8 is set to 100L. Otherwise, the output of biomass electricity in Fig. 8 would not be visible. Moreover, the carbon emission costs would be reduced to 36.7%, although it would still form the most substantial cost of the coproduction plant.



(a)



(b)

Fig. 7. Monthly electricity and bioethanol output in Case 2 (decrease in electricity demand) for (a) the coproduction plant and (b) biomass electricity power plant.

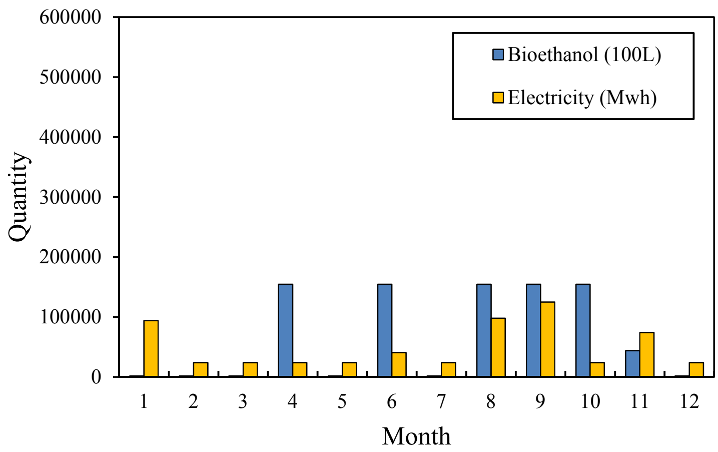


Fig. 8. Monthly electricity and bioethanol output when the revenues from bioethanol and electricity are equal in Case 2.

Table 10. Profit, revenues, and costs in the optimized result when the revenues from bioethanol and electricity are equal in Case 2 (unit: US$ million)

Item	Result
Profit	**13,431,910**
Revenue	**94,847,264**
-Revenue from selling bioethanol	47,423,632
-Revenue from selling electricity	47,423,632
Procurement Cost	**21,365,283**
-Purchase Cost	17,064,294
-Transportation Cost	4,300,989
Carbon Emission Cost	**29,880,971**
Production Cost	**29,878,090**
Ash Handling Cost	**291,010**

3) Case 3: Increase in the carbon emissions cost

In response to intensified global warming and the publication of the Paris Agreement, carbon emission costs may increase and become actual taxes required to be paid for in the future. Thus, this study investigates the optimized simulation results of the coproduction model when carbon emission costs rose by 20%, and verifies the applicability of the model in such a scenario (Case 3).

The results reveal that the optimized profit of the coproduction model is negative when the carbon emission costs increase by 20% (Table 11), which suggests that the model would not have any advantage in this scenario. Because carbon emission costs are one of the key factors to consider, current coproduction plants are not be cost-effective. Indeed, all the existing bioenergy plants have overlooked carbon emission costs, which must be reviewed in response to the growing effects of global warming and climate change. It is clear that more efforts are required to attain the cost-effectiveness of forest bioenergy plants.

Fig. 9 is the monthly electricity and bioethanol output in Case 3, and the total output of electricity is lower than the base case. The total output of electricity is 600000 Mwh in the base case (Fig.3), and the total output of electricity is 519172 Mwh in Case 3. The result indicates that when carbon emissions cost increases, coproduction plant decreases the output of electricity to avoid more loss.

Table 11. Profit, revenues, and costs in the optimized results of coproduction plant and independently operated power plant in Case 3 (unit: US$ million)

Item	Result
Profit	**-22,793**
Revenue	**42,488,437**
-Revenue from selling bioethanol	2,289,611
-Revenue from selling electricity	40,198,826
Procurement Cost	**7,652,233**
-Purchase Cost	6,578,599
-Transportation Cost	1,073,634
Carbon Emission Cost	**31,595,055**
Production Cost	**3,006,348**
Ash Handling Cost	**257,594**

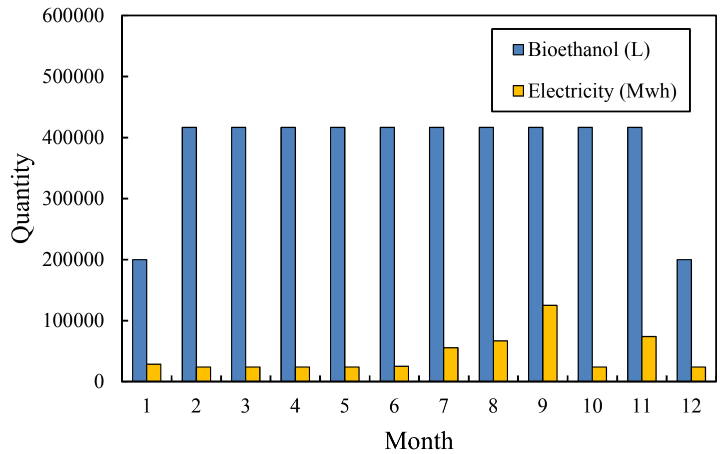


Fig. 9. Monthly electricity and bioethanol output in Case 3.

4.4. Sensitivity analysis

This subsection discusses the effects of various parameters on the profits of coproduction plants. For the manager of a forest biomass electricity and bioethanol coproduction plant, understanding the effects of changes in distinct cost and sale prices on the plant is imperative. Therefore, a sensitivity analysis is conducted on the parameters, and a tornado diagram is produced to identify the most crucial parameters in the model, thereby providing a reference to managers for prioritizing the changes of several cost and sale prices.

The tornado diagram (Fig. 10) depicts the effects of the ± 20% range of parameter change. Specifically, this study designates the monthly electricity (EP_t) and bioethanol (BP_t) prices, respectively US$70 and US$0.5, as the base case scenario to explore the effects of these two parameters on the profit of the model.

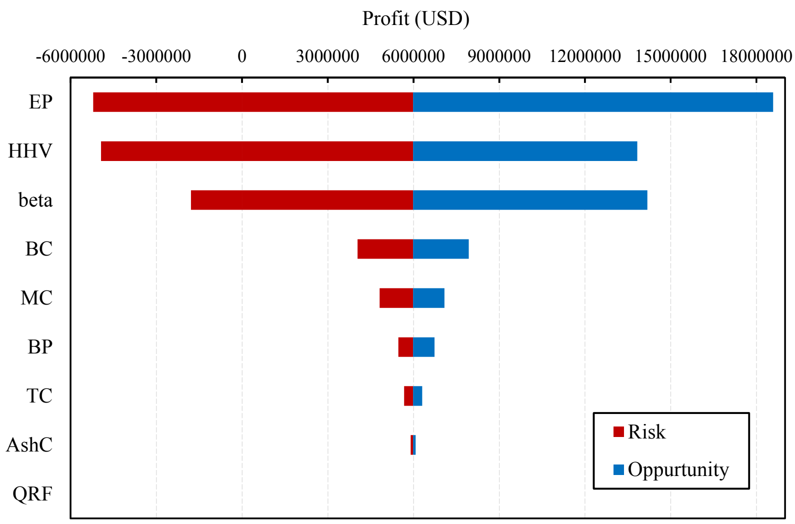


Fig. 10. Tornado diagram for sensitivity analysis.

From Fig. 10, the three most influential parameters are the monthly electricity price (EP_t), the higher heating value of raw materials (HHV), and the unit carbon emission cost (β), with the changes in electricity prices affecting profits most profoundly. Accordingly, plant leaders should prioritize managing electricity prices. The quality of raw materials is also crucial, and the leaders must monitor the quality of the raw materials provided by suppliers. Furthermore, production strategies must be adjusted in response to changes in carbon emission costs. The effect of bioethanol prices (BP_t) on the profit is small, which is attributed to the low bioethanol demand. However, the proportional decline in the energy values of raw materials caused by the storage falling below its lower level (QRF) does not considerably affect the profit of the model because the raw material supply is sufficient and *SLL* is met.

4.5. Discussion

The analysis results indicated that the coproduction model outperformed the independently operated power plant models regarding profit. When the electricity demand was reduced, the coproduction plant could mitigate its losses through the increase in bioethanol output, and when the raw materials were insufficient, the model exhibited no substantial difference from the independent model in profit. However, when the carbon emission costs increased, the coproduction model lost its advantages. Moreover, because of the disparity between the bioethanol and electricity power demand presently, the coproduction model does not have any advantage in its application. For example, when the electricity demand is lowered, the model would mitigate its losses through an increase in bioethanol production; however, because of the lower bioethanol demand, the effect of such mitigation would be limited. Notably, when the current bioethanol production capacity doubles, the coproduction model would outperform the independently operated power plant model in profit, even when faced with raw material insufficiency. Specifically, when the annual bioethanol demand and production capacity reaches 18 million L (3.6 times the current quantity), the bioethanol revenue of the model would equal its electricity revenue (US$4.7 million). Furthermore, the carbon emission costs decreased to 36.7% in this scenario, which is half that of the base case scenario.

According to the sensitivity analysis results, electricity prices were the most critical parameter to the profit of the coproduction model, followed sequentially by the higher heating value of raw materials and unit carbon emission costs. This revealed that changes in electricity prices affect the profit of the model the most profoundly, and plant leaders should prioritize managing electricity prices. The quality of raw materials is also crucial, and leaders must monitor the quality of the materials provided by suppliers. Additionally, production strategies must be adjusted in response to the changes in carbon emission costs.

This study relied on the data generated through simulation to yield results that were as close to actual scenarios as possible. Because no actual cases were available for reference, however, the possible scenarios in reality could not be thoroughly displayed. It is hoped that actual cases become available to improve the credibility of bioethanol and electricity coproduction plants in future studies. Additionally, because electricity prices affect this model the most profoundly, tactical decisions are closely related to electricity prices. Predicting the changes in electricity prices is therefore crucial in developing and operating a forest biomass electricity and second-generation bioethanol coproduction plant.

5. Conclusion

This study employed an MILP model on the tactical supply chain of a forest biomass electricity and second-generation bioethanol coproduction plant. The model differed from those employed in previous studies because it involved a single-input–double-output production pattern, as well as consideration for environmental and carbon emission costs. No actual cases are currently available to investigate through the use of the model; thus, an empirical simulation was conducted to analyze whether the commercial-scale biomass electricity and bioethanol coproduction model exhibits an advantage in the bioenergy industry. Scenario and sensitivity analyses were then performed to examine the problems that might hinder the model, and its decision-making effect, in SCM. In short, this study verified whether the coproduction model can lower associated risks more extensively than the independent plant operation models.

In summary, the forest biomass electricity and second-generation bioethanol coproduction model exhibits considerable profit advantages over the independent electricity and bioethanol production models in the base case scenario. When various uncertainties occur, however, the coproduction model may either maintain or lose its advantages. This is because the bioethanol production capacity and demand cannot mitigate the risks associated with electricity generation in the current industrial environment. Managers that decide to construct forest biomass electricity and second-generation bioethanol plants are advised to examine whether the bioethanol production capacities and demand of the plants are sufficient enough to justify their existence. Furthermore, coproduction plants are not cost-effective when carbon emission costs rise by 20%; this problem must be resolved in researching and developing electricity and bioethanol coproduction plants.

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