Biomass Conversion and Biorefinery (2023) 13:1047–1070
https://doi.org/10.1007/s13399-020-01264-1

ORIGINAL ARTICLE

A mathematical model for optimizing a biofuel supply chain with outsourcing decisions under the carbon trading mechanism

Yasaman Memari[1] · Ashkan Memari[2,3] · Sadoullah Ebrahimnejad[1] · Robiah Ahmad[3]

Received: 8 September 2020 / Revised: 4 December 2020 / Accepted: 29 December 2020 / Published online: 10 January 2021

Abstract
Carbon trading is a market-based mechanism for controlling carbon emissions by providing economic incentives to reduce emissions. In recent years, there has been an increasing interest in modeling supply chain networks under this scheme; however, to date, only a limited number of researchers have investigated the implication of this mechanism for biofuel supply chains. The optimization model presented in this paper examines a trade-off between the cost of trading carbon credits and costs associated with outsourcing of the biomass pretreatment process when carbon emissions exceed the predetermined carbon cap in a biofuel supply chain. To demonstrate the applicability of the model, we analyzed challenges in supplying different sources of biomass to two biorefinery plants and shipping the produced biofuels to multiple demand zones. The results showed that carbon emission reductions have a relatively nonlinear pattern when the carbon credit price increases linearly. Furthermore, we presented significant managerial and policy insights on the impact of different carbon emission caps on total costs and total emissions. Moreover, we analyzed the cost adjustment between trading carbon credits and outsourcing decisions for different carbon cap settings. This paper ends with suggestions for further development of the presented model for future researches.

Keywords Biofuel supply chain · Carbon trading policy · Optimization · Outsourcing · Logistics

Abbreviations

Greenhouse gas	(GHG)
Mixed-integer linear programming	(MILP)

1 Introduction

The phenomenon of gradual global warming and climate change triggered by the high dependency on fossil fuels has become a significant concern for many researchers and policymakers. To date, many efforts have been made to control greenhouse gases' (GHG) emissions. Nevertheless, one of the main obstacles to limiting GHG emissions is the high cost of installation of environmentally friendly technologies [1–3]. Different cost-effective strategies have been introduced to reduce carbon emissions [4]. Carbon tax and emission trading schemes have been widely recognized in various countries as the most cost-effective mechanisms to limit carbon emission [5].

From the supply chain perspective, companies may choose either capacity expansion or outsourcing a part of their production to fulfill the ever-increasing customers' demands. However, more outputs implicitly mean higher emissions [6]. On the other hand, carbon emission reduction decisions usually put companies into a dilemma: to invest in new eco-friendly production technologies or to use renewable energy sources for their energy usage. Many researchers have focused on developing new technologies for clean energy generation [7], e.g., transforming biomass into biofuel. However, far less attention has been paid to a bigger picture: how can the whole supply chain of bioenergy solely align with environmental protection goals? Under the carbon trading scheme, firms can enjoy the profit earning from selling the balance of unused carbon emission credits from their allocated carbon cap. This

✉ Ashkan Memari
ashkan.eng@gmail.com

1 Department of Industrial Engineering, Faculty of Engineering, Islamic Azad University, Karaj Branch, Karaj, Iran

2 Department of Management, Sunway University Business School, Sunway University, Bandar Sunway, Selangor, Malaysia

3 Department of Engineering, Razak Faculty of Technology and Informatics, Universiti Teknologi Malaysia, International Campus, Kuala Lumpur, Malaysia

paper aims to explore the potential solutions for the following circumstance under the cap-and-trade policy. When a company utilizes all its allocated carbon credits, if there is a need for exceeding the carbon cap due to higher demand, what are the optimal solutions? (i) To purchase carbon credits and fulfill this demand using an overproduction option, or (ii) to outsource a part of production or (iii) a combination of both? If so, how much should be allocated to each option?

To address this problem, we developed an optimization model for a multi-period and multi-echelon bioenergy supply chain. We answer this question: when the demand exceeds the allocated carbon cap, how much is the share of outsourcing and overproduction (by purchasing additional carbon credits) in order to minimize the total carbon emission and total costs?

2 Literature review

This paper deals with three main streams of literature: (i) bioenergy supply chain optimization, (ii) optimizing supply chains under the carbon trading scheme, and (iii) supply chain optimization with outsourcing decisions. We elaborate on each stream in the following sections.

2.1 Optimization of bioenergy supply chains

The existing literature on bioenergy supply chain optimization is extensive and devotes more attention to the design of bioenergy supply chains [8]. There is a relatively smaller body of literature concerning bioenergy supply chain planning. For example, Arabi [9] developed a mixed-integer linear programming (MILP) model to minimize the fixed cost of harvesting, pretreatment, treatment, and energy conversion for planning and designing a microalgae-based biobutanol supply chain network. Chen and Fan [10] suggested a mixed-integer stochastic programming model for designing a bioethanol supply chain in uncertain conditions. They extended their model by considering optimal feedstocks resource allocation. Akgul et al. [11] formulated a multi-objective mathematical model to optimize a bioethanol supply chain considering the land utilization requirements. Furthermore, they analyzed the impact of the carbon tax on the considered bioethanol supply chain overall performance. Osmani and Zhang [12] investigated a multi-period biomass-to-bioethanol supply chain using a multi-objective optimization model under uncertain conditions. Moreover, Kim et al. [13] dealt with a model to find the optimum design of a biomass supply chain for biodiesel production. They considered different scenarios to investigate the biofuel network design through the Fischer Tropsch and fast pyrolysis biodiesel conversion processes perspectives in the US. Gong and You [14] proposed an optimization model to design algae-based biodiesel through a life cycle optimization framework. Besides, their suggested model simultaneously determines environmental and economic efficiency. They proved that the net present value could significantly be affected by biodiesel price as well as the environmental impact might be ended up by high fertilizer price. Nodooshan et al. [15] presented a multi-objective optimization model to design a sustainable algal biofuel supply chain. The proposed model minimizes the total cost of the supply chain and the total life cycle of GHG emissions. Ghelichi et al. [16] formulated a two-stage stochastic programming model for a green biodiesel supply chain. In order to evaluate the performance of their model, they investigated a real case study in Iran.

2.2 Optimization of carbon emissions in the planning of supply chain

Several studies have considered a mathematical approach to tackling carbon emissions in the green supply chain. Researchers have looked at carbon emission levels directly in mathematical models. For example, Paksoy et al. [17] proposed a linear mathematical model that minimizes carbon emissions under a carbon tax policy. They investigated various transportation modes to estimate the costs of distribution and transportation of goods in a supply chain. Wang et al. [18] presented a multi-objective optimization model for finding a balance between total costs and environmental impacts in a supply chain planning problem. In their study, the optimization criteria were as follows: (i) the amount of carbon released by production; and (ii) the cost of investment in green facilities and the costs of transportation and transportation available. They used a set of numerical analyses to find Pareto optimal solutions as well as their sensitivity to different parameters. They concluded that the higher capacity of the facility in the supply chain led to an increase in total logistics costs and environmental impacts. These observations were expanded by Harris et al. [19], which showed that optimal design based on costs does not necessarily mean an alternative to carbon emissions. Besides, Mirzapour et al. [20] showed that quality improvement comes at a cost, so it is a matter of finding a balance between economic and environmental concerns. They stated that ecological damage could be reduced if costs increase. Elhedhli et al. [21] studied a three-echelon supply chain comprising manufacturers, distribution centers, and consumers. They used a concave function to calculate the amount of carbon in the supply chain. The optimization results showed that it is possible to change the optimal configuration of a supply chain according to the cost of distribution.

Fahimnia et al. [22] presented a bi-objective mathematical model for optimizing a supply chain. Their model aims to minimize cost and minimize carbon emissions for a real case study in Australia. The analysis of the numerical results obtained in this paper provides insights for managers and legislators that are (i) helping industries to identify essential activities that play a crucial role in the supply chain. (ii) For policymakers, they discussed insights that make carbon prices meaningful and reasonable so that factories can afford to pay for it. In another study [23], they examined the impact of a carbon tax on cost and carbon reduction. A nonlinear model was formulated to identify an optimal solution between transportation costs and carbon emissions. The results of the implemented model showed that the current pricing plan for carbon emissions in Australia might only have a slight increase in total logistics costs, which is not enough to limit carbon emission. Also, they extended their study in 2014 [24], by proposing a single objective optimization model to minimize two conflicting costs: the logistics costs and carbon emission costs. Finally, this paper implemented the carbon tax plan with tactical (mid-term) supply chain planning. The results of their study (a case study in Australia) indicated that maximizing environmental protection through carbon tax is possible.

Zakeri et al. [25] studied a supply chain planning model at the tactical-operational planning level under two carbon taxes and carbon trading schemes. The results of this research indicate that there is a turning point that effectively reduces carbon pricing and carbon trading patterns. Memari et al. [1] presented a mathematical model for a biomass-to-bioenergy supply chain by comparing carbon tax and carbon trading policies. They found that if carbon prices do not precisely set in the carbon tax policy, a carbon tax can significantly increase logistics costs without remarkable (even in some cases ineffectiveness) changes in reducing carbon emissions. Also, the numerical results of their study showed that when carbon prices increase linearly, carbon emission reduction has a nonlinear trend.

2.3 Supply chain optimization with outsourcing consideration

Perry [26] emphasized that a company can obtain competitive advantages, including reliability and quality, through outsourcing. Sharpe [27] explained that outsourcing could reduce the cost of adjustment (improvement) in response to economic change. Improvements were responses to technological innovations, customer preferences changes, or other changes in supply and demand.

Glass and Saggi [28] found that outsourcing would reduce the final cost of production, increase profits, and create more incentives for innovation. Therefore, in comparison with capacity expansion, outsourcing is a way to meet customer orders at a lower final cost, as well as maintaining the flexibility of performance in environmental change.

Ameknassi et al. [29] developed a planning model that combines logistics outsourcing decisions with supply chain strategy planning decisions. The purpose of this paper was to minimize the expected logistics costs and greenhouse gas emissions of a supply chain. The results of this research showed a supply chain configuration that provides decision-makers with optimal levels for integrating logistics outsourcing into supply chain de-carbonation before any low-carbon investment.

Hahn et al. [30] investigated the impact of logistical outsourcing on carbon footprint and related costs. They believed that companies could reduce road transportation to reduce shipping costs through outsourcing. However, road transportation may be time-consuming, and this time depends on the structure of the third-party logistics network, including terminals and communications.

The detailed comparison of the reviewed studies is presented in Table 1.

2.4 Motivation and contribution

This research distinguishes itself from the previous literature in the following ways:

1. The implementation of carbon emission regulations imposes additional costs to firms. In most of the earlier relevant studies, researchers have focused only on implementing policies to reduce carbon emissions. However, the combination of other alternative strategies with carbon emission policies, e.g., outsourcing partial production processes, which can potentially lead to lower total costs with lower carbon emission, has been less investigated. To the best of our knowledge, this issue has rarely been investigated in the body of bioenergy supply chains' literature. The developed mathematical model in this research contributes to all these shortcomings by considering the trade-off between trading carbon credits and partial outsourcing of biofuel production when carbon emissions exceed the carbon cap under the cap-and-trade carbon regulatory.
2. Analysis of the numerical results provides critical managerial implications and policy insights that were difficult to obtain without investigating the presented model in this research (see Sections 4.1 and 4.2).

3 Problem definition

The considered biofuel supply chain in this study is depicted in Fig. 1 The biomass sources such as barley, wheat, sugar cane, sugar beet, maize, and rice, as well as municipal solid wastes, are collected from farms and transported to the collection and pretreatment center. The pretreated feedstock (agricultural wastes and residues) are then shipped to two bioethanol refinery plants for further processing. At the processing level, feedstocks are converted to bioethanol through

Table 1 Summary of the reviewed literature

Author(s)/ Year	Objective (s)	Considered carbon policy			Optimization approach						Findings	Outsourcing decisions
		Carbon tax	Carbon trade	Carbon offset	Integer programming	Linear programming	Nonlinear programming	Mixed-integer linear programming	Mixed-integer nonlinear programming	Programming software		
Balaman et a-l./2014	The purpose of this study is to develop a decision support system (DSS) for the design and management of anaerobic digestion based biomass to energy supply chains in a cost-effective and environmentally friendly manner by tackling inherent uncertainties	✗	✗	✗	✗	✗	✗	✗	✗	Cplex	The results reveal that the proposed model can effectively be used in practice	✗
Arabi et al. /2019	The goal of this study is minimizing the fixed cost of constructing the required facilities, transportation costs, and operational costs (harvesting, pretreatment, treatment, and energy conversion)	✗	✗	✗	✗	✗	✗	✓	✗	–	The results show the validity and usefulness of the proposed model. It is gained a practical supply chain design model by selecting appropriate and accurate candidate areas	✗
Chen et al. /2012	The model is established to support the strategic planning of bioenergy supply chain systems and optimal feedstock resource allocation in an uncertain decision environment	✗	✗	✗	✗	✗	✗	✓	✗	Ampl- Cplex	The model results show that bio-waste-based ethanol can be a viable part of a sustainable energy solution for the future	✗
Akgul et al. /2012	This paper presents a multi-objective, static modeling framework for the optimization of hybrid first/s generation biofuel supply chains	✓	✗	✗	✗	✗	✗	✓	✗	Gams- Cplex	The results highlight the better environmental performance of second-generation biofuel production technologies compared to	✗

Table 1 (continued)

Author(s)/ Year	Objective (s)	Considered carbon policy			Optimization approach						Findings	Outsourcing decisions
		Carbon tax	Carbon trade	Carbon offset	Integer programming	Linear programming	Nonlinear programming	Mixed-integer linear programming	Mixed-integer nonlinear programming	Programming software		
											first-generation by evaluating the potential GHG savings that can be achieved through biofuel production in hybrid facilities that integrate first and second-generation technologies	
Osmani et al. /2017	The objective is to maximize the economic, environmental, and social performance simultaneously	✗	✗	✗	✗	✗	✗	✓	✗	Gams	Results show that in a stochastic environment, it is cost-effective (primarily) and environmentally sustainable (secondarily) to meet up to 20% of Wisconsin's annual demand of gasoline from locally produced bioethanol by using switchgrass as the primary source of biomass feedstock. It also shows	✗
Kim et al. /2011	The objective is to determine the number, location, and size of the two types of processing units and the amount of materials to be transported between the various nodes of the designed network so that the overall	✗	✗	✗	✗	✗	✗	✓	✗	Gams- Cplex	Based on the robustness and GSA, we concluded that the optimized multiple scenario design was able to mitigate the impact of the variation and did not "miss"	✗

Table 1 (continued)

Author(s)/ Year	Objective (s)	Considered carbon policy			Optimization approach						Findings	Outsourcing decisions
		Carbon tax	Carbon trade	Carbon offset	Integer programming	Linear programming	Nonlinear programming	Mixed-integer linear programming	Mixed-integer nonlinear programming	Programming software		
	profit is maximized while respecting the constraints associated with the product demands										any major contributor to the overall profit variation	
Gong et al. /2017	In this study, we develop a consequential life cycle optimization (LCO) framework that simultaneously optimizes consequential environmental impacts and economic performance. We propose a general system boundary that encloses processes linked by markets	✗	✗	✗	✗	✗	✗	✗	✓	–	The proposed model implemented in a real-world case study of producing renewable diesel from microalgae. The study investigated detailed market analysis to identify the consequences connected to the renewable diesel production process.	✗
Nodooshan et al. /2018	In this article, an algal biofuel supply chain network with three echelons of procurement, production, and distribution is modeled with the goal of determining the optimal configuration of the algal biofuel network that minimizes the total supply chain cost and its total GHG emission	✗	✗	✗	✗	✗	✗	✓	✗	Gams- Cplex	The results show that a 420,000-ton reduction in GHG emission can be achieved with 15% increase in the total supply chain cost which is noticeable considering the new challenges the world is facing such as global warming	✗
Pansy et al. /2010	The paper developed and proposed a multi objective mathematical model to solve the green supply chain	✗	✗	✗	✗	✓	✗	✗	✗	Lindo	The focuses of this paper are conducting the minimizing total CO_2 emissions.	✗

Table 1 (continued)

Author(s)/ Year	Objective (s)	Considered carbon policy			Optimization approach						Findings	Outsourcing decisions
		Carbon tax	Carbon trade	Carbon offset	Integer programming	Linear programming	Nonlinear programming	Mixed-integer linear programming	Mixed-integer nonlinear programming	Programming software		
	problems which are emerged because of environmental responsibilities. Paper aimed to minimize the total cost via; 1. minimizing the transportation costs in both forward and reverse logistic, 2. minimizing the total CO2 emission amount, 3. minimizing the total purchasing costs, 4. maximizing the total opportunity profit in the model										Also paper try to encourage the customers to use recyclable materials as an environmental performance viewpoint besides minimizing total costs. To consider the ‘greenness’ and the serious legislations, the traditional structure of the supply chain will be inadequate. This shortage can be solved by assembling a product recovery process as called the closed-loop supply chain	
Wang et al. /2011	The paper propose a multi-objective optimization model that captures the trade-off between the total cost and the environment influence	✗	✗	✗	✗	✓	✗	✗	✗	Cplex	The results show that model can be applied as an effective tool in the strategic planning for green supply chain	✗
Harris et al. / 2011	This paper aims to assess the impact of the traditional cost optimization approach to strategic modeling on overall logistics costs and CO2 emissions by taking into account the supply	✗	✗	✗	✗	✗	✗	✗	✗	✗	The analysis shows that the optimum design based on costs does not necessarily equate to an optimum solution for CO2 emissions; therefore there is a	✗

Table 1 (continued)

Author(s)/ Year	Objective (s)	Considered carbon policy			Optimization approach						Findings	Outsourcing decisions
		Carbon tax	Carbon trade	Carbon offset	Integer programming	Linear programming	Nonlinear programming	Mixed-integer linear programming	Mixed-integer nonlinear programming	Programming software		
	chain structure (number of depots) and different freight vehicle utilization ratios (90%, 75% and 60%)										need to address economic and environmental objectives explicitly as part of the logistics design	
Al-e et al. / 2012	This paper presents a multi-objective model to deal with a multi period multi-product multi-site aggregate production planning problem for a medium-term planning horizon under uncertainty	✗	✗	✗	✗	✗	✓	✗	✗	Gams	The results demonstrate the practicability of the proposed multi-objective stochastic model as well as the proposed algorithm	✗
Elhedhli et al. / 2012	This paper integrates the cost of carbon emissions into supply chain network design. The new problem formulation minimizes the combined expenses associated with the fixed costs to set up a facility, the transportation cost to move goods and the cost of emissions generated on the shipping lanes.	✗	✗	✗	✗	✗	✗	✓	✗	Matlab- Cplex	The test results indicate that considering emission costs can change the optimal configuration of the supply chain, confirming that emission costs should be considered when designing supply chains in jurisdictions with carbon costs.	✗
Fahimnia et al. / 2015	This paper introduces a practical supply chain optimization model that incorporates both economic and carbon emission objectives. The proposed model is implemented to examine the possible	✓	✗	✗	✗	✗	✗	✗	✓	–	Analysis of the numerical results provides important managerial implications and policy insights. For industry practitioners, the findings can assist	✗

Table 1 (continued)

Author(s)/ Year	Objective (s)	Considered carbon policy			Optimization approach						Findings	Outsourcing decisions
		Carbon tax	Carbon trade	Carbon offset	Integer programming	Linear programming	Nonlinear programming	Mixed-integer linear programming	Mixed-integer nonlinear programming	Programming software		
	economic and environmental trade-offs for various carbon-pricing and fuel-pricing scenarios in an actual case company representing the discrete, durable parts manufacturing sector										in identifying the critical activities along the supply chain on which to focus in order to minimize the cost implications of a carbon-pricing regulation	
Fahimnia et al. / 2013	This article investigates the cost implications and carbon reduction potentials of the carbon-pricing scheme in Australia. The model is developed representing the trade-off between transportation costs and the costs of carbon emission and fuel consumption	✓	✗	✗	✗	✗	✗	✗	✓	Cplex	Empirical findings from model implementation in an actual case study suggest that the current carbon-pricing scheme in Australia may only make a minor increase in the overall logistics costs that may be inadequate to drive a significant shift in transport behaviors	✗
Fahimnia et al. / 2015	This paper presents a tactical supply chain planning model that integrates economic and carbon emission objectives under a carbon tax policy scheme	✓	✓	✗	✗	✗	✗	✗	✓	Matlab	The analyses of the numerical results provide important organizational and policy insights on (1) the financial and emissions reduction impacts of a carbon tax at the tactical planning level, (2) the use of cost/emission	✗

Table 1 (continued)

Author(s)/ Year	Objective (s)	Considered carbon policy			Optimization approach						Findings	Outsourcing decisions
		Carbon tax	Carbon trade	Carbon offset	Integer programming	Linear programming	Nonlinear programming	Mixed-integer linear programming	Mixed-integer nonlinear programming	Programming software		
											trade-off analysis for making informed decisions on investments, (3) the way to price carbon for maximum environmental returns per dollar increase in supply chain cost	
Zakeri et al. / 2015	This paper presents an analytical supply chain planning model that can be used to examine the supply chain performance at the tactical/operational planning level under these two policy schemes	✓	✓	✗	✗	✗	✗	✓	✗	Cplex	the results show that there are inflection points where both carbon pricing and trading schemes could influence costs or emissions reductions	✗
Memari et al. / 2018	This paper presents a multi-period bio-energy supply chain under carbon pricing (carbon tax) and carbon trading (cap-and-trade) policies at the tactical planning level. A mixed-integer linear programming model was adopted to optimize the proposed regional oil-palm biomass-to-bio-energy supply chain planning model	✓	✓	✗	✗	✗	✗	✓	✗	Cplex	The numerical results indicate that when carbon pricing is in place when carbon tax increases linearly, carbon emissions' reductions have a nonlinear trend, whereas both cost increase and carbon emissions' reductions have a relatively upward trend in the carbon trading scheme. This paper also presents the sensitivity analysis	✗

Table 1 (continued)

Author(s)/ Year	Objective (s)	Considered carbon policy			Optimization approach						Findings	Outsourcing decisions
		Carbon tax	Carbon trade	Carbon offset	Integer programming	Linear programming	Nonlinear programming	Mixed-integer linear programming	Mixed-integer nonlinear programming	Programming software		
											of the proposed model regarding cost, emissions' generation and supply chain performance	
Glass et al. / 2001	The paper investigates the effects of increased outsourcing of production to a low wage country	✗	✗	✗	✗	✗	✗	✗	✗	–	An increase in production taxes in the North, production subsidies in the South, or a subsidy to adapting technologies has similar effects	✓
Ameknassi et al. / 2016	The paper develops a programming model, which combines logistics outsourcing decisions with some strategic Supply Chains' planning issues, such as the Security of supplies, customer Segmentation, and the Extended Producer Responsibility. The purpose is to minimize both the expected logistics cost and the Green House Gas (GHG) emissions of the Supply Chain (SC) network, in the context of business environment uncertainty	✗	✗	✗	✗	✓	✗	✗	✗	Excel Microsoft	The result is a set of optimal non-dominant green SC configurations, which provide the decision' makers with optimal levels of logistics outsourcing integration within a decarbonized Supply Chain before any further low-carbon investment	✓
Hahn et al. / 2016	The topic is approached from a multi-criteria	✗	✗	✗	✗	✓	✗	✗	✗	Cplex	The paper is highlighted the	✓

Table 1 (continued)

Author(s)/ Year	Objective (s)	Considered carbon policy			Optimization approach						Findings	Outsourcing decisions
		Carbon tax	Carbon trade	Carbon offset	Integer programming	Linear programming	Nonlinear programming	Mixed-integer linear programming	Mixed-integer nonlinear programming	Programming software		
	decision-making perspective, since service, cost, quality, and more long-term value-related aspects need to be considered to arrive at well-balanced decisions										benefits of the approach and to investigate tactical trade-offs when coordinating internal and external manufacturing decisions	

biochemical or thermochemical technologies. Finally, the produced biofuels are sent to the two main customers' zones.

3.1 Model formulation

The mathematical model presented here deals with the minimization of total costs, and the overall carbon emission originated from production, storage, distribution, and transportation in a multi-period supply chain. When biofuel demand exceeds the specified carbon cap for the pretreatment center, the collected biomass sources (feedstocks) are outsourced to a third-party collection and pretreatment center for processing, and they are directly shipped to biorefinery plants once being processed. It should be noted that the collection and pretreatment center of the considered case study emits more carbon in the processing of feedstocks due to its older machinery and technology compare to the third-party pretreatment center. However, the processing costs in this center are lower compared to the third-party pretreatment center. The third-party pretreatment center operates with more modern technology with lower carbon emissions and higher processing costs. The goal is to develop a mathematical model that originated economic and environmental costs for the T planning horizon. The following assumptions were considered in developing the mathematical model:

- The end-users' demand is deterministic.
- The location and capacity of the collection and pretreatment centers and biorefinery plants are known.
- Shortage is allowed.
- The transportation cost is proportional to the traveling distance.

The following indices are used to formulate the problem.

$i = 1, \ldots, I$ Biorefinery plant index

$j = 1, \ldots, J$ Biofuel demand zone index

$t = 1, 2, \ldots, T$ Time period index

The input parameters include the following:

D_{jt} Forecasted demand for bioethanol in demand zone j in period t (ton)

PC_t Biomass processing cost at collection and pretreatment center in period t (\$/ton)

OC_t Biomass processing overproduction cost (when exceeding the permitted cap) at collection and pretreatment center in period t (\$/ton)

OUC_t Biomass processing cost in the third-party pretreatment center (outsourcing cost) in period t (\$/ton)

HC_t Pretreated biomass holding cost at collection and pretreatment center in period t (\$/ton)

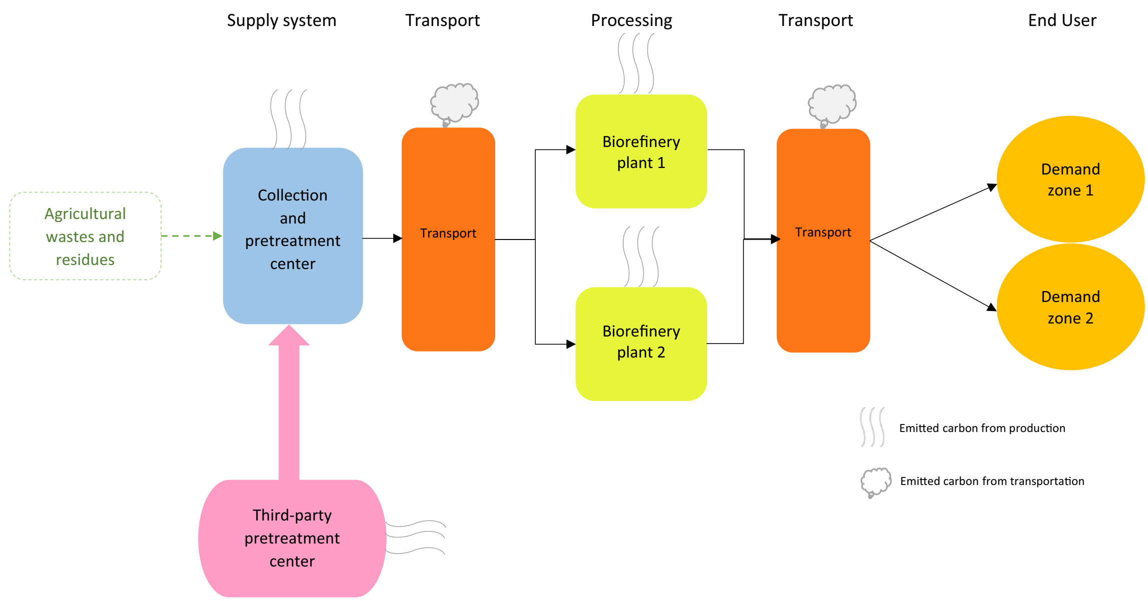

Fig. 1 The considered biofuel supply chain

$H'C_{it}$	Bioethanol holding cost in the biorefinery plant i in period t (\$/ton)
SC_{it}	Pretreated biomass transportation cost from collection and pretreatment center to biorefinery plant i in period t (\$/ton)
$S'C_{ijt}$	Bioethanol shipping cost from biorefinery plant i to demand zone j in period t (\$/ton)
BC_{jt}	Bioethanol backorder cost at demand zone j in period t (\$/ton)
K_t	Processing capacity of collection and pretreatment center in period t (ton)
K'_t	Third-party pretreatment center processing capacity in period t (ton)
M_t	Maximum inventory holding capacity in collection and pretreatment center in period t (ton)
M'_{it}	Maximum inventory holding capacity of biorefinery plant i in period t (ton)
E_t	Estimated carbon emissions to produce one ton of bioethanol in period t (kg/ton)
E'_t	Estimated carbon emissions to process one ton of biomass pretreatment in the third-party pretreatment center in period t (kg/ton)
ES_{it}	Estimated carbon emissions for the shipment of feedstock from collection and pretreatment center to biorefinery plant i in period t (kg/ton.km)
$E'S_{ijt}$	Estimated carbon emissions for the shipment of bioethanol from biorefinery plant i to demand zone j in period t (kg/ton.km)
EH_t	Estimated carbon emissions for holding one ton of pretreated biomass in period t (kg)
$E'H_{it}$	Estimated carbon emissions for holding one ton of bioethanol in biorefinery plant i in period t (kg)
Cap_t^{Max}	Maximum allowed carbon emissions (carbon cap) in period t (kg)
ρ	Proposed carbon price (\$/kg)
$Sell_{Max}$	Maximum selling amount of carbon credits (kg)
DIS_i	Distance between collection and pretreatment center and biorefinery plant i (km)
DIS'_{ij}	Distance between biorefinery plant i and demand zone j (km)

Decision variables include the following:

X_t	Amount of pretreated biomass at collection and pretreatment center in period t (ton)
Y_t	Amount of bioethanol production when carbon emissions exceed the carbon cap in period t (ton)
G_t	Amount of outsourced biomass to third-party pretreatment center in period t (ton)
R_{it}	Amount of pretreated biomass shipped from collection and pretreatment center to biorefinery plant i in period t (ton)
W_{ijt}	Amount of bioethanol delivered to demand zone j from biorefinery plant i in period t (ton)
L_t	Inventory amount of pretreated biomass at collection and pretreatment center at the end of period t (ton)
N_{it}	Inventory amount of pretreated biomass (feedstock) in biorefinery plant i at the end of period t (ton)
Q_{jt}	Amount of incurred shortage of bioethanol at demand zone j at the end of period t (ton)
TE_t	Total amount of emitted carbon in period t (kg)
B_t^+	Amount of purchased carbon credits in period t (kg)
B_t^-	Amount of carbon credits sold in period t (kg)

Considering the defined parameters and decision variables, a linear programming model was used to formulate the supply chain network aiming to minimize logistics costs and carbon emission costs. The logistics costs (Eq. (1.1)) include processing costs at the collection and pretreatment center during regular production and also when carbon emissions exceed the permitted carbon limit (components 1 and 2), outsourcing costs (component 3), inventory holding costs at the collection and pretreatment center, bioethanol refinery plants (parts 4 and 5), the transportation costs (components 6 and 7), and shortage costs (component 8).

$$Min\ Z_1 = \sum_{t=1}^{T} X_t * PC_t + \sum_{t=1}^{T} Y_t * (OC_t + (E_t * \rho)) + \sum_{t=1}^{T} G_t * OUC_t + \sum_{t'=1}^{T} L_{t'} * HC_{t'} + \sum_{i=1}^{I}\sum_{t'=1}^{T} N_{it'} H'C_{it'} + \sum_{i=1}^{I}\sum_{t=1}^{T} R_{it} * SC_{it} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} W_{ijt} * S'C_{ijt} + \sum_{j=1}^{J}\sum_{t'=1}^{T} Q_{jt'} * BC_{jt'} \tag{1.1}$$

The second objective Eq. (1.2) indicates the carbon emission, which includes the emitted carbon from the production (component 1), the carbon emitted by the transportation activities (components 2 and 3), the carbon emission in storage (components 4 and 5) the amount of purchased and sold carbon credits (components 6 and 7).

$$Min\ Z_2 = \sum_{t=1}^{T} X_t * E_t + \sum_{i=1}^{I}\sum_{t=1}^{T} R_{it} * DIS_i * ES_{it} + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{t=1}^{T} W_{ijt} * DIS'_{ij} * ES'_{ijt} + \sum_{t=1}^{T} L_t * EH_t + \sum_{i=1}^{I}\sum_{t=1}^{T} N_{it} * E'H_{it} + \sum_{t=1}^{T} B_t^{+} - \sum_{t=1}^{T} B_t^{-} \tag{1.2}$$

Since the objective in both objective functions is to minimize the cost (overall logistics costs and carbon emission costs ,(the goal is to minimize the overall cost of the supply chain. Given the goal of minimizing logistics costs and carbon emission costs, the second part of the objective function can be defined as in Eq. (1.3):

$$Z = Min\left(Z_1 + (\rho * Z_2)\right) \tag{1.3}$$

The objective functions in Eq. (1.3) is subject to the following constraints:

Constraint (2) indicates the holding capacity constraint for in the collection and pretreatment center, and the capacity limitation of the third-party pretreatment center is presented in Constraint (3).

$$X_t + Y_t \le K_t \quad \forall t \tag{2}$$

$$G_t \le K'_t \quad \forall t \tag{3}$$

Inventory capacity at the collection and pretreatment center is shown in Constraint (4) and Constraint (5) formulates the inventory capacity at biorefinery plants.

$$L_t \le M_t \quad \forall t \tag{4}$$

$$N_{it} \le M'_{it} \quad \forall i, t \tag{5}$$

Constraint (6) and Constraint (7) model the inventory flow conservation t in collection and pretreatment center and biorefinery plants respectively at the end of the period of t.

$$L_t - L_{t-1} = X_t + Y_t + G_t - \sum_{i=1}^{I} R_{it} \quad \forall t \tag{6}$$

$$N_{it} - N_{i(t-1)} = R_{it} - \sum_{j=1}^{J} W_{ijt} \quad \forall i, t \tag{7}$$

Constraint (8) and Constraint (9) ensure supply limitation and demand satisfaction in biofuel demand zones.

$$\sum_{i=1}^{I} W_{ijt} = D_{jt} - Q_{jt} + Q_{j(t-1)} \quad \forall j, t \tag{8}$$

$$\sum_{t=1}^{T} X_t + \sum_{t=1}^{T} Y_t + \sum_{t=1}^{T} G_t = \sum_{j=1}^{J}\sum_{t=1}^{T} D_{jt} \tag{9}$$

Constraint (10) calculates the emitted carbon from the production, transportation, and holding of inventory at both collection and pretreatment center and biorefinery plant and the carbon emission limitations for purchasing and selling is defined by Constraint (11).

$$TE_t = \left(X_t * E_t + \sum_{i=1}^{I} R_{it} * DIS_i * ES_{it} + \sum_{i=1}^{I}\sum_{j=1}^{J} W_{ijt} * DIS'_{ij} * E'S_{ijt} + (L_t * EH_t) + \sum_{i=1}^{I} N_{it} * E'H_{it} \right) \quad \forall t \tag{10}$$

$$TE_t = Cap_t^{Max} - B_t^{-} + B_t^{+} \quad \forall t \tag{11}$$

Constraint (12) identifies the amount of in-house production and outsourcing when the total supply chain carbon emission exceeds the permitted carbon emission cap.

$$\left(\left(Y_t{*}E_t\right)+\left(G_t{*}E'_t\right)\right)=B_t^+ \quad \forall t \tag{12}$$

Constraint (13) shows the maximum carbon credit that the collection and pretreatment center can sell to other firms and companies.

$$B_t^- \le Sell_{Max} \quad \forall t \tag{13}$$

Constraints 14, 15, 16, and 17 guarantee the non-negativity value of decision variables:

$$X_t, Y_t, G_t, L_t, TE_t, B_t^+, B_t^- \ge 0 \quad \forall t \tag{14}$$

$$R_{it}, N_{it} \ge 0 \quad \forall i, t \tag{15}$$

$$Q_{jt} \ge 0 \quad \forall j, \mathrm{t} \tag{16}$$

$$W_{ijt} \ge 0 \quad \forall i, j, t \tag{17}$$

In general, Integer Programming (IP) is NP-complete [31, 32]. Theoretically, IP is a special case of Mixed-Integer Programming (MIP), so MIP is at least as hard as IP. On the same basis, we can argue that the formulated problem in this study is at least NP-complete (if it is not an NP-Hard problem), and Cplex can efficiently solve this problem.

3.2 Model verification and validation

The MILP model was initially coded and run in CPLEX 12.7.1. Then, to validate the proposed model's accuracy and coding, we coded and ran the model in Lingo 15.0. For the validation purpose, we considered a supply chain, including a pretreatment center, two biorefinery plants ($I=2$), and two demand zones ($J=2$) in two periods planning horizon ($T = 2$). The used parameters for running of the mathematical model can be found in Appendix 1.

The obtained results from CPLEX and LINGO are presented in Tables 2 and 3, respectively.

In order to evaluate the validity of the mathematical model and to compare the results, we defined an index for measuring the error between both software results. We called this measure the percentage of error and defined it as follow Eq. (18):

$$\mathrm{Error}\% = \frac{Lingo\ Z - Cplex\ Z}{Cplex\ Z} {*}100 \tag{18}$$

The results comparison showed only 0.002% and 0.0001% difference between the obtained value for the first objective function second objective with both software, respectively.

4 Sensitivity analysis

4.1 Sensitivity analysis based on carbon credit price

Table 4 consists of two components of costs (logistics costs + carbon emissions cost) and carbon emissions cost. In this regard, various carbon prices ranging from \$0 to \$80 per ton of carbon emissions in intervals of \$5 were considered. Each row in this table shows a fixed carbon price. The carbon emissions components include three logistic operations: production, inventory holding, and transportation.

In the first row ($\rho=0$), we considered a baseline in which there was no carbon emission restriction (Cap_{Max} and carbon credit price was considered 0). In this case, the total carbon emission is 146,890 tons (the maximum carbon emission, as there is no restriction for carbon emission in the model). Figure 2 shows the cost of supply chain versus carbon emissions for a range of different carbon prices. As can be seen, by increasing carbon prices from \$0 to \$80, logistic costs increase steadily and relatively linearly.

As it is evident in Fig. 2, when carbon credit prices increase, emission reduction has a nonlinear trend. A rapid decline in emissions spreads between \$0–10 per ton of carbon emissions. After this point (the carbon price of \$10), carbon emissions have declined steeply, and from \$60 upwards, the carbon emission remains unchanged. In general, rising in carbon prices are resulting in cost increase and carbon emissions reduction. Table 5 illustrates the amount of overproduction versus the amount of biomass outsourcing to the third-party pretreatment center for carbon price ranges of \$0–\$80 per ton of carbon emission.

As shown in Fig. 3, when carbon prices increase within the ranges of \$0–\$40 per ton of carbon emission, the total costs rise by 97.69%, and the total emissions fall by 8.89%. Moreover, when carbon price ranges from \$40–\$80, the total costs increase by 98.82%, and the total emissions remain steady and unchanged. We can conclude that if reducing carbon emission is the only important objective for organizations and policymakers, the best way to price carbon is the beginning price in which the carbon emissions reduction remains almost steady.

According to Fig. 4, as carbon prices increase, the total amount of outsourced biomass to the third-party pretreatment center rises accordingly. In contrast, the amount of pretreated biomass in the company's pretreatment center decreases. Moreover, when carbon price ranges from \$5 to \$20 per ton of carbon emission, as carbon credit prices increase, the total amount of over-production in the company's pretreatment center reduces by 64.9%. Within the price ranges of \$20–\$50 per ton of carbon emission, the amount of overproduction indicates 67.3% that it shows a slower reduction rate than the price ranges of \$5–\$20, and after \$50, the amount of overproduction remains fixed and unchanged. Moreover,

Table 2 Optimizing results using lingo software

Decision variables					
X_t	Amount	Y_t	Amount	G_t	Amount
X_1	555	Y_1	–	G_1	–
X_2	109	Y_2	226	G_2	–
L_t	Amount	TE_t	Amount	B_t^+	Amount
L_1	45	TE_1	11,996	B_1^+	3.97
L_2	–	TE_2	12,902	B_2^+	2
B_t^-	Amount	R_{it}	Amount	N_{it}	Amount
B_1^-	–	R_{11}	410	N_{11}	120
B_2^-	904	R_{12}	380	N_{12}	–
–	–	R_{21}	100	N_{21}	100
–	–	R_{22}	–	N_{22}	–
W_{ijt}	Amount	Q_{jt}	Amount	–	–
W_{111}	100	Q_{11}	–	–	–
W_{112}	150	Q_{12}	–	–	–
W_{121}	190	Q_{21}	–	–	–
W_{122}	350	Q_{22}	–	–	–
W_{211}	–	–	–	–	–
W_{212}	–	–	–	–	–
W_{221}	100	–	–	–	–
W_{222}	–		–	–	–
The amount of objective function					
Total costs (Z1)			Total emissions (Z2)		
1110.2			24,898		

Table 3 Optimizing results using Cplex software

Decision variables					
X_t	Amount	Y_t	Amount	G_t	Amount
X_1	555	Y_1	–	G_1	–
X_2	109	Y_2	226	G_2	–
L_t	Amount	TE_t	Amount	B_t^+	Amount
L_1	45	TE_1	11,996.03	B_1^+	3.97
L_2	–	TE_2	12,902	B_2^+	2
B_t^-	Amount	R_{it}	Amount	N_{it}	Amount
B_1^-	–	R_{11}	410	N_{11}	120
B_2^-	904	R_{12}	380	N_{12}	–
–	–	R_{21}	100	N_{21}	100
–	–	R_{22}	–	N_{22}	–
W_{ijt}	Amount	Q_{jt}	Amount	–	–
W_{111}	100	Q_{11}	–	–	–
W_{112}	250	Q_{12}	–	–	–
W_{121}	190	Q_{21}	–	–	–
W_{122}	250	Q_{22}	–	–	–
W_{211}	–		–	–	–
W_{212}	–		–	–	–
W_{221}	100		–	–	–
W_{222}	–		–	–	–
The amount of objective function					
Total costs (Z_1)			Total emissions (Z_2)		
1110.230			24,898.03		

when carbon price ranges from \$5 to \$20 per ton of carbon emission, the amount of outsourced biomass to the third-party pretreatment center increased up to 42%, and after the price of \$25, the amount of outsourced biomass remains steady.

In general, when total carbon emissions of the considered supply chain exceeds from the predetermined carbon cap (Cap_{max}); if the objective is only to minimize carbon emissions, outsourcing of pretreatment process in the range of carbon price between \$10–\$80 is more wise choice compare to the over-production option, as it reduces a significant amount of carbon emission.

4.2 The sensitivity analysis of carbon trading

Using the concept of grandfathering, we examined the impact of various carbon caps on total costs. For this purpose, we began without considering the carbon cap and tightened the carbon cap to achieve the most possible carbon emission reduction with a trial-and-error approach. Table 6 shows the numerical results of this investigation. This table shows total costs and total emissions in the range of 2% grandfathering (shown in column 1) and carbon cap (shown in column 2). At the starting point (the baseline) and when there is no limit for carbon emissions, the total emissions is 146,890 tons (refer to the first row of Tables 4 and 5). The grandfathering of 2% indicates the carbon trading price of \$0.1 is required to reduce 2% of carbon emission (the total emissions from 146,890 tons to 143,952 tons) as a new carbon cap. According to the current structure of the considered supply chain, available technologies and equipment, the lowest possible carbon emission reduction rate is 10,282 tons, which is equal to 84% grandfathering. In other words, the maximum total carbon emission considered for the case study is 16%, and to achieve this value, the carbon trading price of \$3.29 per ton of carbon should be considered.

Figure 5 illustrates the trend of total logistics costs and total carbon emissions for each grandfathering percentage. As shown in Fig. 5, logistic costs are increased by limiting the carbon cap. This is mainly due to purchasing extra carbon credits for fulfilling the demand. When grandfathering reduces by 16% (from 100 to 84%), overall costs are increased by about 83%, and carbon emissions are decreased by about 16%. By decreasing the percentage of grandfathering, there is a continuous and gradual decrease in carbon emissions, so that the supply chain costs increases continuously.

Figure 6 shows the estimated carbon prices for each of the grandfathering percentages which were determined on a trial-and-error basis. Reducing the percentage of grandfathering

Table 4 Computational results for different carbon pricing

Carbon Price	Cost components ($)							Total logistics cost	Emission components (ton)			Total emission
	Production	Over Production	Outsourcing	Holding	Transportation	Backlog	Emission		Production	Holding	Transportation	
0	5/2317	0	0	0	2/2343	126,490	131,150.7	131,625	20,600	0	126,290	146,890
5	3/1293	29,477	1810	372/39	5/2359	144,950	690,780	870,709	11,496	27/373	126,290	138,159
10	1/1358	37,433	2460	332/85	2/2285	212,850	1,349,800	1,606,272	12,072	652	122,260	134,984
15	4/1405	348,994	2916	05/102	7/2265	247,620	2,011,400	2,300,703	12,492	30/831	120,770	134,093
20	1400	39,202	3116	37/102	7/2265	258,920	2,678,900	2,983,906	12,444	93/832	120,670	133,947
25	4/1400	48,517	3120	44/102	5/2265	259,390	3,348,500	3,663,295	12,448	56/834	120,660	133,943
30	1409	55,769	3120	08/102	5/2265	265,410	4,016,000	4,344,076	12,524	30/831	120,510	133,865
35	3/1410	64,524	3120	39/101	5/2265	266,520	4,685,000	5,022,941	12,536	41/826	120,490	133,852
40	2/1411	73,321	3120	87/101	7/2265	268,070	5,353,500	5,701,790	12,544	67/829	120,460	133,834
45	1413	81,857	3120	89/101	6/2265	269,620	6,022,000	6,380,377	12,560	67/829	120,444	133,834
50	5/1413	90,474	3120	90/101	5/2265	269,620	6,691,400	7,058,395	12,564	67/829	120,440	133,834
55	5/1413	99,454	3120	72/101	7/2264	269,770	7,360,500	7,736,624	12,564	04/828	120,440	133,832
60	5/1413	108,340	3120	39/101	5/2265	269,830	8,029,500	8,414,570	12,564	41/826	120,440	133,830
65	5/1413	117,410	3120	39/101	5/2265	270,230	8,698,600	9,093,140	12,564	41/826	120,440	133,830
70	5/1413	126,390	3120	39/101	5/2265	269,740	9,367,800	9,770,830	12,564	41/826	120,440	133,830
75	5/1413	135,070	3120	39/101	5/2265	270,050	10,037,000	10,449,020	12,564	41/826	120,440	133,830
80	5/1413	144,350	3120	39/101	5/2265	269,770	10,706,000	11,127,020	12,564	41/826	120,440	133,830

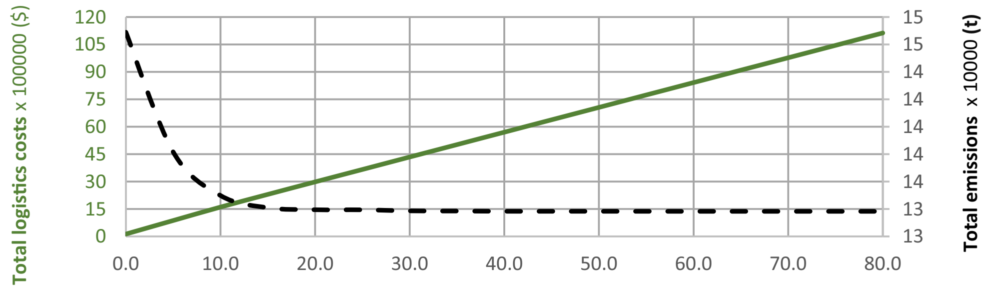

Fig. 2 Total logistics cost vs. total carbon emissions for different carbon prices

leads to an increase in carbon prices. To reduce carbon emissions to 16% (84% grandfathering target), it is necessary to raise carbon prices to $2.39 per ton of carbon emission. It should be noted that in practice, the purchasing and selling of carbon credit prices are determined based on demand and supply in the market. Also, the final price of carbon in the market significantly depends on the performance of other companies participating in the carbon trading scheme. On the other hand, governments and policymakers can influence the actual carbon market price by adjusting the carbon cap.

Table 7 presents the numerical results for the amount of over-production in the company's collection and pretreatment center and the amount of outsourcing biomass for the pretreatment process in the third-party pretreatment center based on different grandfathering percentages. As can be seen from the results, when the carbon cap reduces from 146,890 to 141,014 tons, pretreatment outsourcing seems unwise due to its high costs. Also, by reducing the percentage of grandfathering (reducing the carbon cap from 146,890 to 123,388 tons), the amount of over-production in the company's collection and pretreatment center increases from 2023 to 3074 tons. Similarly, the amount of outsourcing increases from 0 to 1560 tons. In such a situation, pretreating of biomass in the company's pretreatment center is a more economical alternative.

Figure 7 compares the amount of pretreated biomass in the over-production at the company's collection and pretreatment center with the amount of outsourced biomass to be pretreated in the third party pretreatment center under a different carbon cap. According to Fig. 7, by limiting the carbon emission cap, more carbon credits need to be purchased to fulfill the demand, which causes higher costs. When the carbon cap ranges from 143,952 to 141,014 tons, the results indicate that purchasing 8092 to 8846 tons of carbon credits is a more cost-effective alternative. By tightening the carbon cap to 123,388

Table 5 Numerical results for the amount of over-production vs. of biomass outsourcing to the third-party pretreatment center for different carbon prices

Carbon price	Overproduction (Y_t)		Outsourcing (G_t)	
	Amount of biomass	Percentage of reduction	Amount of biomass	Percentage of increase
0	0	–	0	–
5	1371	0	905	0
10	902	34.2	1230	26.4
15	569	58.5	1458	37.9
20	481	64.9	1558	41.9
25	478	65.1	1560	42
30	459	66.5	1560	42
35	456	66.7	1560	42
40	454	66.9	1560	42
45	452	67	1560	42
50	449	67.3	1560	42
55	449	67.3	1560	42
60	449	67.3	1560	42
65	449	67.3	1560	42
70	449	67.3	1560	42
75	449	67.3	1560	42
80	449	67.3	1560	42

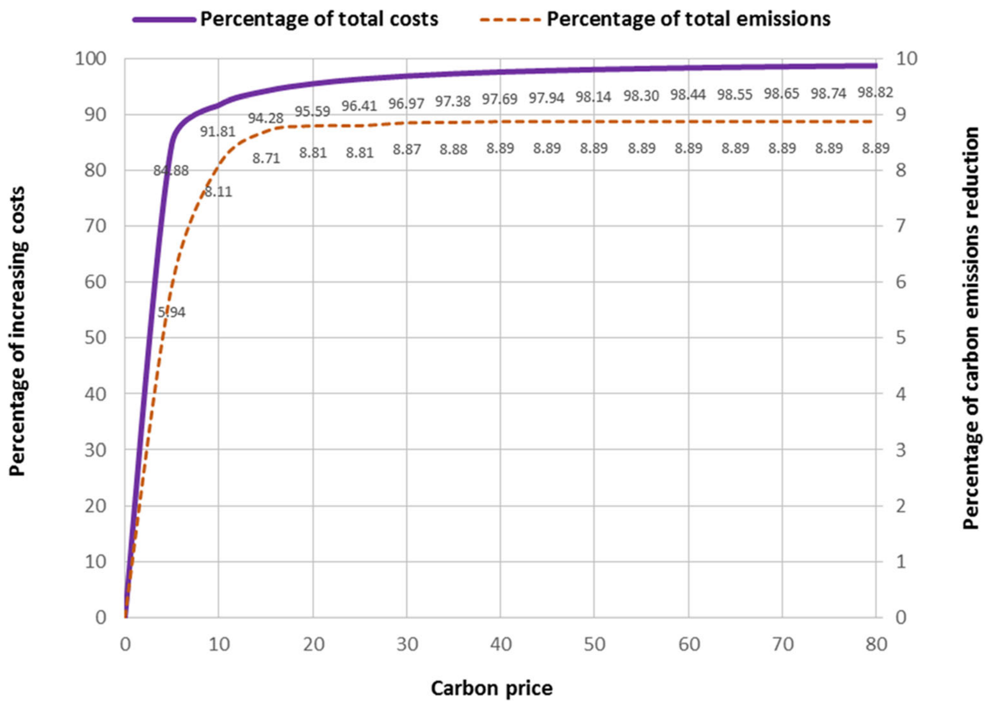

Fig. 3 Percentage of total logistics costs vs. the percentage of total carbon emissions for different carbon prices

tons, the amount of biomass outsourcing to the third-party center increases to 1560 tons. In such a situation, the optimization results show buying 3074 tons of carbon credits (for over-production) and purchasing 15,416 tons of carbon credits.

4.3 Comparison between previous researches and the current research

According to the reviewed literature in Section 2, previous researchers usually focused on strategic decisions for design bioenergy supply chains [9, 11–13, 15]. In addition, previous researchers usually tended to find a balance between cost and carbon emission in optimizing bioenergy supply chains [4, 10, 19, 21, and]. As there are many issues related to tactical decisions, this research considered a bioenergy supply chain with focusing more on tactical decisions. Besides, in order to control and reduce emitted carbon, we analyzed the problem under the carbon emission trading scheme, while the common way in the literature is minimizing carbon emission and total costs simultaneously (finding a balance or eco-efficient optimal answers). Few studies investigated biomass supply chain under carbon trading (e.g., [1]); however, the role of outsourcing is almost ignored in all of them.

5 Conclusions

Over the last decade, increasing GHG emissions and tackling climate change have become a significant challenge for governments. Many countries have introduced and implemented policies to reduce GHG emissions.

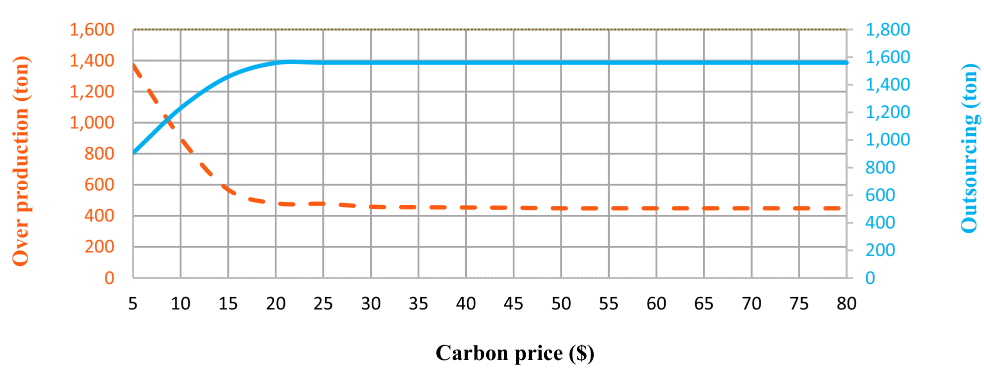

Fig. 4 The amount of outsourced biomass to the third-party pretreatment center vs. the amount of biomass processed in the company's pretreatment center when carbon emission exceeding the carbon cap for different carbon price ranges

Table 6 Numerical results for carbon trading

Percentage grandfathering	Carbon cap (year/ton)	Carbon cap per period	Desired carbon price ($)	Emission components			Total carbon emissions	(B^+)The amount of carbon purchases	(B^-)The amount of carbon sales
				Production	Holding	Transportation			
100	146,890	12,241	0	20,600	0	126,290	146,890	0	0
98	143,952	11,996	1/0	12,508	1/2515	126,290	141,313	8092	–10,735
96	141,014	11,751	1/0	11,736	3/2135	126,290	140,161	8864	–7/9718
94	138,077	11,506	3/0	9384	1/2039	126,290	137,713	10,814	–11,177
92	135,139	11,262	7/2	8232	2/391	126,290	134,913	10,652	–10,875
90	132,201	11,017	73/5	6348	51/451	125,050	131,850	11,584	–11,943
88	129,263	10,772	6/6	6140	42/707	122,200	129,047	11,608	–11,824
86	126,325	10,527	8/16	4416	2/880	120,660	125,956	13,066	–13,434
84	123,388	10,282	2/39	2064	46/883	120,440	123,387	15,416	–15,416

Percentage grandfathering	Cost components								Total cost
	Production	Over production	Outsourcing	Holding	Transportation	Backlog	The cost of carbon purchases	Carbon sales revenue	
100	5/2317	0	0	0	2/2343	126,490	0	0	131,625
98	1/1407	3843	0	840/442	3/2363	118,870	809	–1074	126,662
96	3/1320	4210	0	090/373	5/2359	113,380	886	–972	121,557
94	7/1055	7028	402	020/359	9/2359	110,190	3244	–335	124,304
92	1/926	27,478	1716	256/41	5/2359	116,390	28,760	–29,363	148,309
90	15/714	54,432	2668	068/55	9/2359	140,650	66,376	–68,433	196,822
88	8/690	61,073	2852	188/91	22,847	171,850	76,613	–78,038	257,978
86	8/496	170,860	3118	040/107	5/2266	210,010	219,509	–225,691	380,676
84	2/232	486,610	3120	690/107	4/2266	264,830	604,307	–604,307	757,166

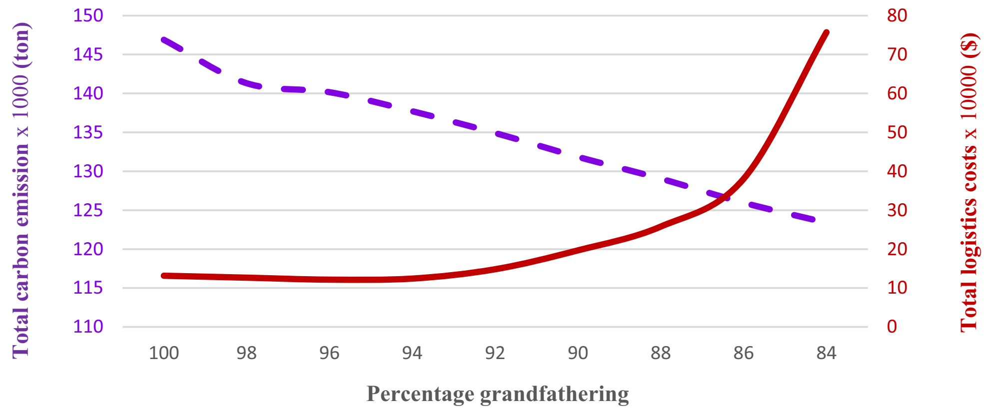

Fig. 5 Total logistics cost vs. total carbon emission for different grandfathering levels

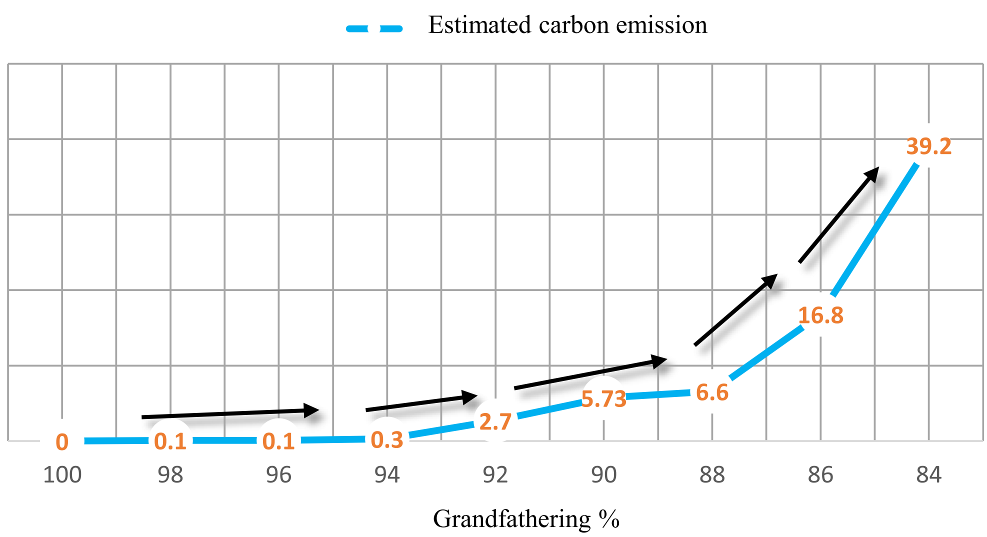

Fig. 6 Estimated carbon prices for each grandfathering goal

Carbon pricing and carbon trading are among the most cost-effective mechanisms in reducing carbon emissions. We developed a mathematical model to find the optimal decision for a biofuel supply chain under the carbon trading scheme. The considered supply chain comprises a biomass pretreatment center, two biorefinery plants,

Table 7 Numerical result for the amount of pretreated biomass in the company's collection and pretreatment center and the third-party pretreatment center with different grandfathering percentages

Percentage of grandfathering	Carbon cap (Year/Ton)	Carbon cap per period	Amount of			Percentage of			Total
			Production	Overproduction	Outsourcing	Production	Overproduction	Outsourcing	
100	146,890	12,241	5150	0	0	100	0	0	100%
98	143,952	11,996	3127	2023	0	60.7	39.3	0	100%
96	141,014	11,751	2934	2216	0	57	43	0	100%
94	138,077	11,507	2346	2603	201	45.6	50.6	3.9	100%
92	135,139	11,262	2062	2234	858	40	43.4	16.9	100%
90	132,201	11,017	1587	2229	1334	30.8	43.3	25.9	100%
88	129,263	10,772	1535	2189	1426	29.8	42.5	27.7	100%
86	126,325	10,527	1104	2487	1559	21.4	48.3	30.3	100%
84	123,388	10,282	516	3074	1560	10	59.7	30.3	100%

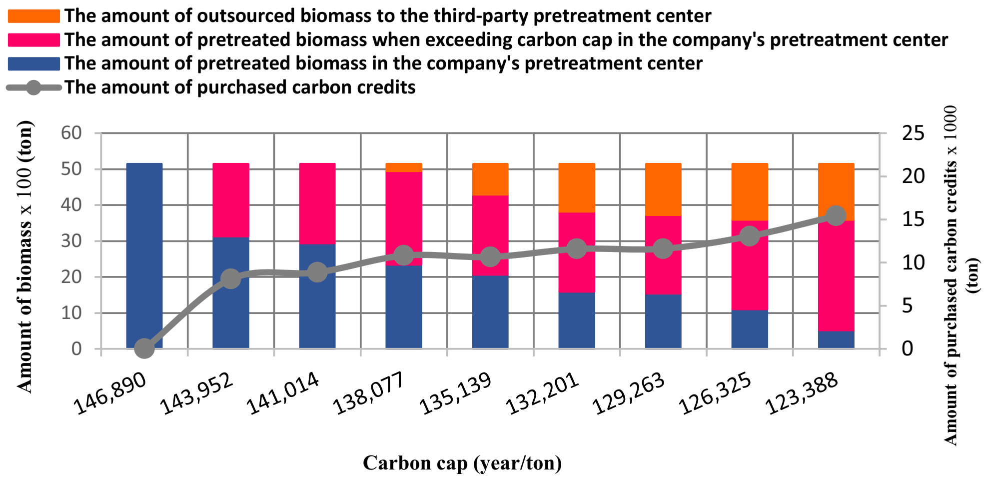

Fig. 7 Carbon cap analysis (in tons)

and two customers demand zones. We investigated the trade-off between outsourcing a part of the pretreatment process and trading carbon credits for pretreating the biomass in over-production time. Subsequently, a sensitivity analysis was carried out concerning various carbon prices and carbon and its impact on the outsourcing pretreatment process and over-production considering various ranges of carbon prices; the results showed that with higher carbon prices, outsourcing is more economical. On the other hand, reducing the carbon cap could lead to a significant increase in costs if other factors were fixed. This study found that rising carbon prices results in cost increase and carbon emissions reduction linearly, which is in line with the findings by [1, 25]. In line with their investigations, the findings of this research were also indicated that a wider carbon emission cap leads to reduce total costs. In addition, we found by decreasing the percentage of grandfathering; there is a continuous and gradual decrease in carbon emissions so that the supply chain costs increase continuously.

5.1 Limitations

The generalization of the obtained results is limited to the assumptions mentioned in Section 3.1. However, there are other limitations in this study that may affect the generalizability of the results; they are:

1. In this study, end-users' demand was considered deterministic. However, considering stochastic and uncertain demand for end-users will affect the results and findings. One of the possible impacts of uncertain demand might be higher carbon emissions as more frequent delivery is needed.
2. Shortage is allowed in the developed mathematical model. If the shortage is not allowed, one most likely scenario is higher carbon allowances (carbon cap) is needed since more inventories are also needed to cover any unexpected demand.
3. The developed model is based on a three-echelon supply chain network. Considering additional echelons (such as end-users) in the considered supply chain network may affect the results of this study.
4. The developed model is formulated with linear integer programming. In the further developing of the proposed model, care should be taken for nonlinear models in which variables and parameters are not linear. The nonlinear behavior of parameters and variables would also result in different findings.

5.2 Future research directions

This research has thrown up many questions in need of further investigation. Further studies need to be carried out considering different transportation modes (such as rails) with different carbon emissions. Future research could also be conducted to determine the impact of social factors on a closed-loop supply chain for lifecycle cradle-to-cradle management in this study's proposed model. In addition, the presented model in this study can be extended to incorporate other sustainability measures, such as water use, and traffic, social impact and it can be implemented in other regions. Another immediate extension of this work is to include uncertainties rooted in carbon emissions evaluation and possibly triggered human-made disasters or by natural fluctuations. Implement other carbon emissions reduction policies such as carbon offset, inflexible carbon cap, and carbon tax would be other interesting directions for future research.

Appendix 1: Data

Table 8 Dataset for demand (ton)

Demand					
$j=1$	D_{jt}	Amount	$j=2$	D_{jt}	Amount
	D_{11}	100		D_{21}	190
	D_{12}	250		D_{22}	350
	D_{13}	350		D_{23}	540
	D_{14}	250		D_{24}	490
	D_{15}	100		D_{25}	120
	D_{16}	200		D_{26}	320
	D_{17}	250		D_{27}	380
	D_{18}	0		D_{28}	200
	D_{19}	100		D_{29}	180
	$D_{1,10}$	150		D_{210}	190
	D_{111}	100		D_{211}	130
	D_{112}	100		D_{212}	110

Table 9 Dataset for inventory capacity in collection and pretreatment center and at biorefinery plant (ton)

Inventory capacity							
M_t	Amount	$i=2$	M'_{it}	Amount	$i=2$	M'_{it}	Amount
M_1	150		$M'_{1,1}$	120		$M'_{2,1}$	100
M_2	200		$M'_{1,2}$	190		$M'_{2,2}$	190
M_3	90		$M'_{1,3}$	200		$M'_{2,3}$	110
M_4	250		$M'_{1,4}$	110		$M'_{2,4}$	180
M_5	100		$M'_{1,5}$	90		$M'_{2,5}$	120
M_6	130		$M'_{1,6}$	180		$M'_{2,6}$	250
M_7	190		$M'_{1,7}$	160		$M'_{2,7}$	220
M_8	220		$M'_{1,8}$	120		$M'_{2,8}$	170
M_9	260		$M'_{1,9}$	250		$M'_{2,9}$	180
M_{10}	280		$M'_{1,10}$	220		$M'_{2,10}$	150
M_{11}	120		$M'_{1,11}$	180		$M'_{2,11}$	140
M_{12}	110		$M'_{1,12}$	110		$M'_{2,12}$	100

Table 10 Carbon emission data (kg/ton)

Carbon emissions				
Produce (kg/ton)	E_t	$\forall t$		4
	E'_t			2
Holding (kg)	EH_t	$\forall t$		0.271
	$E'H_{it}$	$i=1$		
		$i=2$		
Shipment (kg/ton.km)	ES_{it}	$i=1$		1.63
		$i=2$		
	$E'S_{ijt}$	$j=1$	$i=1$	
			$i=2$	
		$j=2$	$i=1$	
			$i=2$	
Carbon credit (kg)	$Sell_{Max}$			1500

Table 11 GHG emission data

GHG emissions item	CO_2
Acquisition (*g/dry ton*) of biomass	22.037
Forest residues (*g/ton*) production	56.184
Transportation (*g/km/ton*)	2.426

Table 12 Distances (km)

Distances			
DIS_i	$i=1$		35
	$i=2$		40
DIS'_{ij}	$j=1$	$i=1$	53
		$i=2$	57
	$j=2$	$i=1$	48
		$i=2$	52

Table 13 Dataset for costs ($/ton)

Costs				
Processing	PC_t	$\forall t$		0.45
	OC_t			1.5
	OUC_t			2
Holding	HC_t	$\forall t$		0.324
	$H'C_{it}$	$i=1$		0.18
		$i=2$		0.15
Transportation	SC_{it}	$i=1$		0.210
		$i=2$		0.293
	$S'C_{ijt}$	$j=1$	$i=1$	0.245
			$i=2$	0.245
		$j=2$	$i=1$	0.325
			$i=2$	0.325
Backorder	BC_{jt}	$j=1$		41
		$j=2$		56

Table 14 Dataset for processing capacity (*ton*)

Processing capacity			
K_t	Amount	K'_t	Amount
K_1	1050	K'_1	80
K_2	1050	K'_2	120
K_3	1284	K'_3	200
K_4	1166	K'_4	150
K_5	1284	K'_5	90
K_6	1050	K'_6	120
K_7	1284	K'_7	140
K_8	1166	K'_8	170
K_9	1166	K'_9	160
K_{10}	1284	K'_{10}	110
K_{11}	1166	K'_{11}	95
K_{12}	1284	K'_{12}	125

References

1. Memari A, Ahmad R, Rahim ARA, Jokar MRA (2018) An optimization study of a palm oil-based regional bio-energy supply chain under carbon pricing and trading policies. Clean Techn Environ Policy 20(1):113–125
2. Hosseini SE, Wahid MA, Aghili N (2013) The scenario of greenhouse gases reduction in Malaysia. Renew Sust Energ Rev 28:400–409
3. Hosseini SE, Wahid MA (2012) Necessity of biodiesel utilization as a source of renewable energy in Malaysia. Renew Sust Energ Rev 16(8):5732–5740
4. Wu J, Ma C, Tang K (2019) The static and dynamic heterogeneity and determinants of marginal abatement cost of CO2 emissions in Chinese cities. Energy 178:685–694
5. Shuai C, Chen X, Wu Y, Tan Y, Zhang Y, Shen L (2018) Identifying the key impact factors of carbon emission in China: results from a largely expanded pool of potential impact factors. J Clean Prod 175:612–623
6. Li J, Su Q, Ma L (2017) Production and transportation outsourcing decisions in the supply chain under single and multiple carbon policies. J Clean Prod 141:1109–1122
7. Awudu I, Zhang J (2012) Uncertainties and sustainability concepts in biofuel supply chain management: a review. Renew Sust Energ Rev 16(2):1359–1368
8. Balaman ŞY, Selim H (2014) A fuzzy multi-objective linear programming model for design and management of anaerobic digestion based bioenergy supply chains. Energy 74:928–940
9. Arabi M, Yaghoubi S, Tajik J (2019) A mathematical model for microalgae-based biobutanol supply chain network design under harvesting and drying uncertainties. Energy 179:1004–1016
10. Chen CW, Fan Y (2012) Bioethanol supply chain system planning under supply and demand uncertainties. Transport Res E-Log 48(1):150–164
11. Akgul O, Shah N, Papageorgiou LG (2012) An optimisation framework for a hybrid first/second generation bioethanol supply chain. Comput Chem Eng 42:101–114
12. Osmani A, Zhang J (2017) Multi-period stochastic optimization of a sustainable multi-feedstock second generation bioethanol supply chain− A logistic case study in Midwestern United States. Land Use Policy 61:420–450
13. Kim J, Realff MJ, Lee JH (2011) Optimal design and global sensitivity analysis of biomass supply chain networks for biofuels under uncertainty. Comput Chem Eng 35(9):1738–1751
14. Gong J, You F (2017) Consequential life cycle optimization: general conceptual framework and application to algal renewable diesel production. ACS Sustain Chem Eng 5(7):5887–5911
15. Nodooshan KG, Moraga RJ, Chen SJG, Nguyen C, Wang Z, Mohseni S (2018) Environmental and economic optimization of algal biofuel supply chain with multiple technological pathways. Ind Eng Chem Res 57(20):6910–6925
16. Ghelichi Z, Saidi-Mehrabad M, Pishvaee MS (2018) A stochastic programming approach toward optimal design and planning of an integrated green biodiesel supply chain network under uncertainty: A case study. Energy 156:661–687
17. Paksoy T, Özceylan E, Weber GW (2010) A multi objective model for optimization of a green supply chain network. In: AIP Conference Proceedings, vol 1239, No. 1. American Institute of Physics, pp 311–320
18. Wang F, Lai X, Shi N (2011) A multi-objective optimization for green supply chain network design. Decis Support Syst 51(2):262–269
19. Harris I, Naim M, Palmer A, Potter A, Mumford C (2011) Assessing the impact of cost optimization based on infrastructure modelling on CO2 emissions. Int J Prod Econ 131(1):313–321
20. Mirzapour SMJ, Aryanezhad MB, Sadjadi SJ (2012) An efficient algorithm to solve a multi-objective robust aggregate production planning in an uncertain environment. Int J Adv Manuf Technol 58(5–8):765–782
21. Elhedhli S, Merrick R (2012) Green supply chain network design to reduce carbon emissions. Transp Res Part D: Transp Environ 17(5):370–379
22. Fahimnia B, Sarkis J, Boland J, Reisi M, Goh M (2015) Policy insights from a green supply chain optimisation model. Int J Prod Res 53(21):6522–6533
23. Fahimnia B, Reisi M, Paksoy T, Özceylan E (2013) The implications of carbon pricing in Australia: an industrial logistics planning case study. Transp Res Part D: Transp Environ 18:78–85
24. Fahimnia B, Sarkis J, Choudhary A, Eshragh A (2015) Tactical supply chain planning under a carbon tax policy scheme: a case study. Int J Prod Econ 164:206–215
25. Zakeri A, Dehghanian F, Fahimnia B, Sarkis J (2015) Carbon pricing versus emissions trading: a supply chain planning perspective. Int J Prod Econ 164:197–205
26. Perry CR (1997) Outsourcing and union power. J Lab Res 18(4):521–534
27. Sharpe M (1997) Outsourcing, organizational competitiveness, and work. J Lab Res 18(4):535–549
28. Glass AJ, Saggi K (2001) Innovation and wage effects of international outsourcing. Eur Econ Rev 45(1):67–86
29. Ameknassi L, Aït-Kadi D, Rezg N (2016) Integration of logistics outsourcing decisions in a green supply chain design: a stochastic multi-objective multi-period multi-product programming model. Int J Prod Econ 182:165–184
30. Hahn GJ, Sens T, Decouttere C, Vandaele NJ (2016) A multi-criteria approach to robust outsourcing decision-making in stochastic manufacturing systems. Comput Ind Eng 98:275–288
31. Papadimitriou CH, Steiglitz K (1998) Combinatorial optimization: algorithms and complexity. Dover, Mineola
32. Garey MR, Johnson DS (1979) Computers and Intractability: a Guide to the Theory of NP-Completeness. In: W.H. Freeman and Company, New York