RESEARCH ARTICLE

Optimization and analysis of a bioelectricity generation supply chain under routine and disruptive uncertainty and carbon mitigation policies

Mahsa Saghaei[1] | Mohammad Dehghanimadvar[2,3] | Hamed Soleimani[4,5] |
Mohammad Hossein Ahmadi[6] (iD)

[1]Young Researchers and Elites Club, Qazvin Branch, Islamic Azad University (IAU), Qazvin, Iran

[2]Department of Renewable Energy and Environment, Faculty of New Sciences and Technologies, University of Tehran, Tehran, Iran

[3]School of Photovoltaic and Renewable Energy Engineering, University of New South Wales, Sydney, NSW, Australia

[4]School of Mathematics and Statistics, University of Melbourne, Parkville, VIC, Australia

[5]Department of Industrial Engineering, Faculty of Industrial and Mechanical Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran

[6]Faculty of Mechanical Engineering, Shahrood University of Technology, Shahrood, Iran

Correspondence

Mohammad Hossein Ahmadi, Faculty of Mechanical Engineering, Shahrood University of Technology, Shahrood, Iran.
Email: mohammadhosein.ahmadi@gmail.com

Abstract

Increasing greenhouse gas emissions and negative environmental consequences have raised worldwide attention to ecological issues. The development of carbon regulations (CRs) beside carbon capture and storage (CCS) systems is part of carbon mitigation policies (CMPs), which are following in recent years to control and manage carbon liberation. Along with environemtal policies, the utilization of renewable energy resources have been promoted significantly. However, the economic opportunities for renewable energy development considering CMPs have not addressed extensively. In this study, a stochastic mathematical programming model has been presented to minimize cost and downside risk (DSR) of the bioelectricity generation supply chain considering the pre- and postdisaster conditions. The role of several CMPs on the economic behavior of the system has been analyzed by investigating the potential uncertainties on material availability, material quality, and consumer demand. To consider disruption effects, the postdisaster stage has been classified into several substages including damage, recovery, and back to the sustainability stages. Mississippi State after the Katrina Hurricane is addressed as a case study to examine the performance of the proposed model. The results demonstrated that the occurrence of disruptive uncertainties creates 8,978,502 \$, 8,864,335 \$ and 8,884,055 \$ as the DSR, under carbon tax policy (CTP), carbon offset policy (COP), and CCS, respectively. The effect of disruptive scenario 1 with a 15% reduction of resource has led to the greatest postdisaster supply chain costs in comparison with other scenarios. Although the financial analysis showed CTP has the greatest DSR after the occurrence of disaster, this policy has the most investment attractions, as well as COP, with the internal rate of return (IRR) of 9%. While implementing the CCS policy with the IRR of 2% creates 7% missed opportunity costs compared with other CMPs.

KEYWORDS

biomass, carbon regulation, CCS, disruption, optimization, Stochastic programming, uncertainty; downside risk

1 | INTRODUCTION

Increasing global carbon emissions and the negative environmental consequences have led to greater adoption and commitment to environmental policies to reduce CO_2 emissions. At the same time, the use of renewable energy resources and cleaner fuels is being pursued with greater speed and enthusiasm.[1–3] Among different types of renewable resources, forest biomass has characteristics that make it one of the viable options for biofuel or bioenergy production.[4,5] Variations in type, availability throughout the year, ability to store and improve its quality with changes in chemical or physical properties are the most important indicators of forest biomass to use for bioenergy production.[6–10]

However, there are several problems with using forest biomass in energy applications. In particular, the rate of carbon emission during woody biomass combustion is significantly higher than the rate of carbon absorption over its growth cycle. This phenomenon, on a large scale, can affect the balance between the amounts of released and absorbed carbon in the atmosphere. Hence, this challenge causes a barrier for utilizing the forest biomass for energy production.[11,12]

Due to environmental concerns, the carbon mitigation policies (CMPs) are seriously implemented for controlling and reducing CO_2 emission over the recent years.[13–16] CMP adoption gains rapid attention due to their direct effects on the economic, social, and environmental feasibility of future renewable energy resources.[17,18] In this regard, several carbon regulations (CRs) have been developed with prevention and control (PC) mechanisms to include limitations, financial penalties or subsidies on the volumes of liberated or captured CO_2. Despite their benefits, there are various issues for implementing CMPs. Variability in energy intensity and utilization by consumers, incompatibility with elasticity in energy demand over time, and lack of financial attractiveness for private investors make shortages in CR implementation.[19,20]

To deal with these problems, alternative CMP strategies such as carbon capture and storage (CCS) have been introduced as a more sustainable option for many industrial communities.[21,22] Contrary to CRs, which impose specific monitoring and limitations on industrial activities, CCS focuses on capturing the exhaust gas of production units and transferring to the storage site.[23,24] In other words, CRs are based on a PC approach, while CCS is an option to treat and improve (TI) postrelease carbon liberation. Although there are various CCS technologies such as precombustion, postcombustion, and oxyfuel can be selected regarding social, economic, and environmental targets,[25,26] the configuration of the CCS system is a challenge, particularly by considering the existence of uncertain factors.

Generally, the bioenergy supply chain is subject to routine and disruptive uncertainties. Routine uncertainties are diverse but predictable, such as normal fluctuation in material availability, consumer demand, and weather conditions.[27,28] While predicting and controlling routine uncertainties are more manageable, disruptive events could have detrimental effects on systems performance through damaging impacts on various elements of bioenergy supply chains. These damages can cause financial loss and investment risk besides stakeholder's reluctance to invest in bioenergy projects.

Given the effects of uncertainties on the economic efficiency of the bioenergy supply chain, this research aims to measure bioenergy supply chain cost under disruptive scenarios, considering the acceptable level of downside risk (DSR) for investors. Along with uncertainty and risk effects, the impacts of implementing different CMPs such as carbon offset policy (COP) and carbon tax policy (CTP) as PC-based approaches, and CCS approach as a TI-based concept are employed to measure the economic feasibility of a bioelectricity generation supply chain.

To incorporate uncertain factors into the model (eg variability in the availability and quality of materials, and diversification of consumer demand), a two-stage stochastic programming model is provided. In this model, the strategic decisions are made in the first-stage and tactical decisions such as resource allocation, carbon capturing, energy generation, material storing, and electrical distribution are structured in the second stage.

For the effective presentation of uncertainty impacts, the postdisaster decision-making space is classified into the damage, recovery, and back to suitability substages, so that the uncertain parametric behavior of the system during these substages is different. The validity of the proposed model is then tested based on data and parameters obtained for the state of Mississippi in the face of Hurricane Katrina. Accordingly, the financial analysis is performed to determine the investment payback period and system profitability under each CMPs.

The remainder of this paper is organized as follows. Section 2 provides a brief review of the related work on modeling uncertainty in bioenergy supply chains and CMP applications. The model is formulated in Sections 3 and 4. The case study, computational results, and economic analysis are presented in Sections 5 and 6. Finally, conclusions and directions for future research are provided in Section 7.

2 | LITERATURE REVIEW

In this section, a brief review of measuring and modeling uncertainty in bioenergy supply chains with a focus on nondeterministic mathematical programming models has been discussed. Then, relevant studies of implementing CMPs on the supply chain structures are reviewed. Accordingly,

the research gap and contributions of this research are highlighted at the end of this chapter.

Generally, the bioenergy supply chain is contained a wide range of activities from material cultivation and harvesting, material processing, storage, transportation, and conversion to transform biomass to bioenergy.[29–31] While the existing literature covers economic, environmental, and social aspects of biomass utilization for energy generation,[32,33] the majority of literature focuses on the optimization of economic objectives using mathematical programming.[34] In this context, optimization models for supplier selection,[35] network configuration,[36–38] logistical decisions, conversion technology selection,[39] vehicle routing,[40] and supply chain uncertainty coverage[29,41,42] are the most popular issues, which are discussed by vast of researchers recently.

Stochastic, fuzzy, and robust optimization models are the most nondeterministic modeling approaches that have been employed widely in recent researches. In this regard, the concepts of the energy life cycle and carbon emission were assessed in a study by Ref. [43. In this research, a biobjective mixed integer programming (MIP) model was developed to cover uncertainties of feedstock availability, transportation capacity, yield, and downside demand. Fattahi and Govadian[44] addressed a multistage stochastic programming model to mitigate greenhouse gas emissions and optimize the social impacts of a biomass-based supply chain under material supply uncertainty.

By presenting a robust optimization model, Babazadeh[45] optimized the total economic performance of the supply chain considering cost minimization and growth of carbon trade under uncertainties. A robust multiobjective model addressed by Ref. [46] to highlight the effects of uncertain factors on the sustainability and risk attitudes of decision-makers in a biofuel supply chain. Saghaei et al. formulated a two-stage stochastic programming model combined with chance constraint and storage limitations to consider the uncertainty of material availability, material quality, and consumer demand in a bioelectricity supply chain. The authors presented the model in both small and large scales and provided basic and improved cross-entropy algorithms to solve them.

In addition to the external uncertainties, the adoption of CMPs imposes new constraints or environmental costs to the system that complicates the decision-making. To indicate the effects of CMPs, Ortiz-Gutiérrez et al.[47] proposed a mixed integer linear programming (MILP) model to develop a bioethanol supply chain under demand uncertainty and GHG savings. They showed that the increment of CO_2 allowance price leads to a reduction in the economic profitability of the system.[48,49] provided a mathematical model to analyze the impacts of several CRs, including carbon cap, carbon tax, carbon cap and trade, and carbon offset schemes on the performance of a biofuel supply chain. In another paper,[50] introduced a MILP model considering carbon tax and carbon

trading (cap-and-trade) regulations in a bioenergy supply chain. Their results demonstrated that change of the carbon price has led to fluctuated emission rend that had not steady behavior.

Along with CR effects, the impacts of CCS technologies on the mitigation of carbon and performance of the supply chain have been attention recently. In this regard, the roles of CCS implementation on the emission level, electricity, price and system's financial behavior have been highlighted by recent researches.[51–53]

According to reviewed literature, uncertainty plays a key role in the performance of the bioelectricity supply chains. On another side, environmental considerations such as the CMPs increase the complexity of decision-making and reduce the economic profitability of bioenergy production. Therefore, studying the effects of uncertainty and environmental considerations on the attraction of investment for stakeholders in the bioenergy projects is necessary.

In this regard, this study presents a two-stage stochastic programming model to minimize the costs of a bioenergy generation supply chain under uncertainty and several CMPs. In our presented model, investment and technical cost elements are formulates in the postdisaster conditions, so that the facility establishment decisions are made as to the first (strategic) stage, and decisions related to the material flow, material storage, and level of generated electricity are formed in the second (tactical) stages under disruption scenarios.

To better incorporate uncertainty effects, the second decision-making stage has classified into three substages after the disaster, to show the effects of damage, recovery, and back to sustainability phases on the tactical decisions.

Our presented model not only focuses on the minimization of supply chain cost but also it is following the reduction of DSR as a variable dependent on the gap of optimal decision costs between pre- and postdisaster conditions. In this way, to consider risk concepts, we have defined DSR constraints in our model.

All formulations are performed in a case study in the southeast area of the Mississippi State to analyze the effects of Katrina hurricane disruptions on the construction of a bioelectricity production project. Finally, due to the net present value (NPV) concepts, a financial analysis is provided to evaluate economic feasibility and missed opportunity of the project regarding several CMPs.

3 | MODEL FORMULATION

In this study, a bioenergy supply chain is configured considering supply areas, material storage locations, power plant locations, and electrical consumer sectors. Firstly, a two-stage stochastic programming model is formulated to minimize the postdisaster supply chain costs (PoSCC) with attention to the

uncertainty of material availability, material quality, and consumer demand under DSR considerations.

DSR variable is calculated simultaneously with PoSCC, regarding defined upper and lower bounds of risk, where the upper bound is the maximum acceptable level of DSR, and lower bound is the gap between PoSCC and an Ideal target for investors. One of the innovations of this study is suggesting the calculating of predisaster supply chain cost (PrSCC) as the ideal target for investors under routine uncertainties.

In this regard, Figure 1 demonstrates the schematic view of the bioenergy generation network. According to this figure, flows of the harvested materials move from supply areas to the storage locations as the green or salvaged woods.

In the storage, air-drying operations use to reduce about 50% of moisture content (MC) of woody materials. In each period, some amounts of dried materials are maintained in the storage as the safety stock to coping with the material shortage in the future. In the next step, the dried feedstocks are sent from storage to the power plant to convert to the electricity and then distributing in the power network.

Affecting by routine uncertainties such as fluctuations of weather conditions, forest resource availability usually is changing. On the other side, the quality of green woods is determined regarding the rate of MC and higher heating value (HHV) that are constantly changeable proportional to the weather indicators such as humidity and temperature. Although supply chain parametric behavior is predictable under routine uncertain conditions, the occurrence of a

sudden event such as natural disasters can significantly influence its performance. In this regard, Figure 2 demonstrates the three separate substages after the disaster.

After the occurrence of catastrophe, time interval a_1 is known as the damage substage, when the large part of the green materials is destroyed in the following the disaster. Therefore, salvaged materials with lower quality will replace in the supply areas. During the recovery stage (a_2), natural or artificial recovery processes will start. In this stage, due to a reduction of the salvaged wood, the stored or new harvested green materials will resupply. Gradually with the regrowing of green materials, the balance between supply and demand will form and system behavior returns to the sustainable level before the disaster (a_3).

Changes in the parametric behavior of the system after the disaster can affect the supply chain decision-making process. In another word, the costs of the optimal decisions over the postdisaster phase are different in comparison with the routine conditions.

In general, supply chain decisions are made in three strategic (long-term), tactical (midterm), and operational (short-term) levels. Strategic decisions are those types of decisions that will be considered prior to observe uncertainty in the system. For example, in the bioelectricity production supply chain, the location and size of power plants and storages are decisions that prospective investors make them, here and now, without considering occurrence the probable uncertainty in the future.
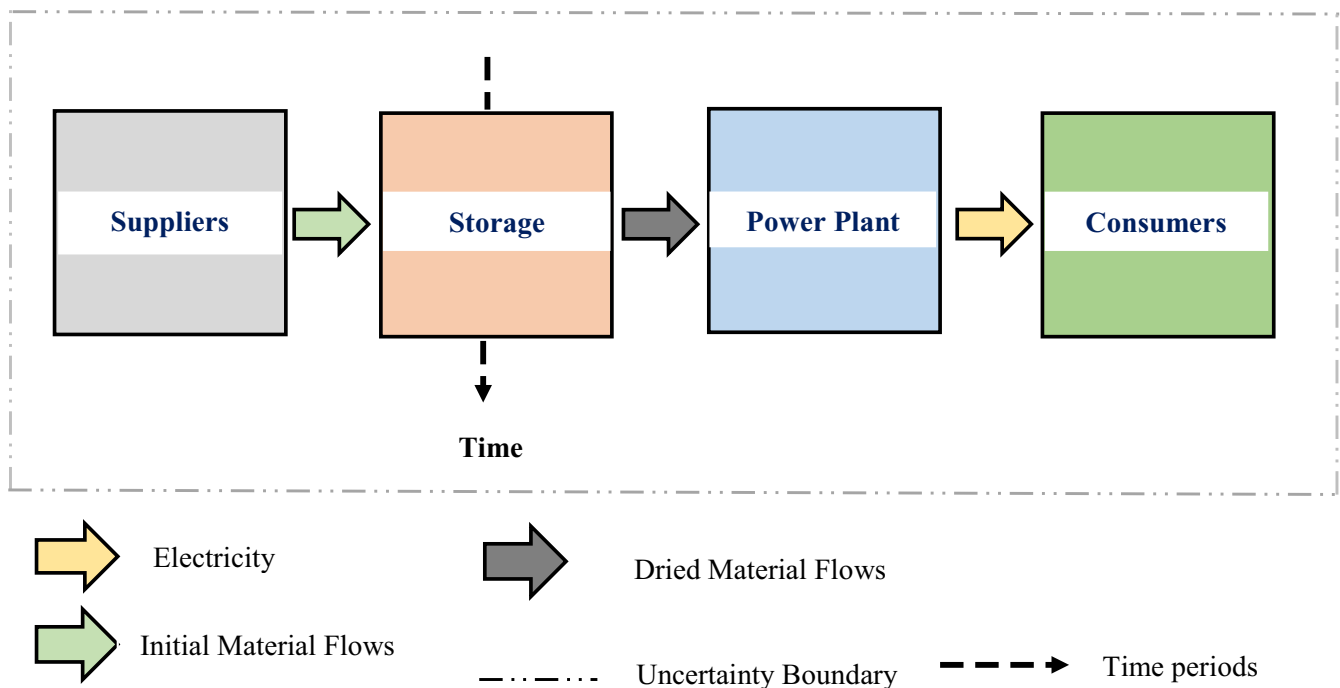

FIGURE 1 The schematic configuration of bioenergy generation supply chain
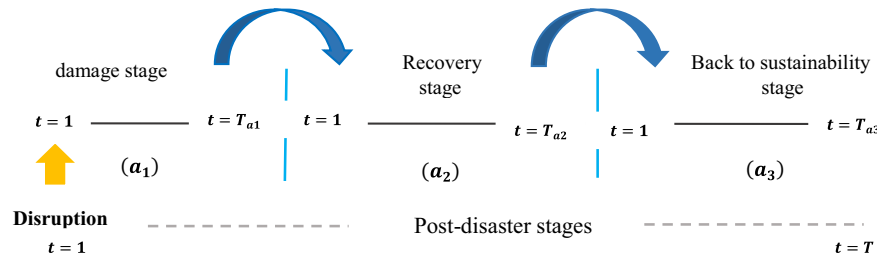
FIGURE 2 Categorization of supply chain behavior after the disaster

On the other hand, tactical decisions such as the amount of material harvested and transported, the amount of stored material and produced electricity are time-dependent decisions that can be affected by disruption scenarios in the future. For instance, uncertainty can influence the level of available biomass resources and the quality of them.

Therefore, in this study, we have employed a two-stage stochastic programming model to optimize the PoSCC. In this way, strategic decisions (size and location of facilities) will be made in the first stage, and tactical decisions (material flows, the level of stored material, and the level of electricity generation and distribution) will be offered proportional to the uncertain scenarios in the second stage.

In this regard, a model is developed to minimize PoSCC, where SC is the cost of first stage (strategic decisions), pr^s is the probability of occurrence of disruptive scenario s, and TC^s is the second-stage decisions (technical decisions) costs (Equation 1).

$$MinPoSCC = SC + \sum_s pr^s * (TC^s) \qquad (1)$$

$$SC = \sum_k \sum_b \left[ic_{kb} + fc_{kb}\right] * x_{kb} \qquad (2)$$

decisions) costs including harvesting, holding, and transportation costs of materials as well as the variable O&M cost of the power plant to generate electricity.

Subject to

$$\text{First} - \text{stage steratgic constraints} \qquad (4)$$

$$\text{Second} - \text{stage tactical constraints} \quad \forall S \in s \qquad (5)$$

$$\text{DSR constraints} \quad \forall S \in s \qquad (6)$$

According to Equations 4 to 6, the constraints of the problem are classified into the first stage, second stage, and DSR constraint groups. In continue, the constraints of each class are presented.

First-stage strategic constraints are including.

$$\sum_b \sum_k xk_{bk} \leq P_1 \qquad (7)$$

$$\sum_i \sum_r xi_{ir} \leq P_2 \qquad (8)$$

Equations 7 and 8 create limitations on the opening or establish material storages and power plants, with attention to the permitted locations and sizes.

$$\begin{aligned}
\sum_s (pr^s * TC^s) = \sum_s (pr^s * [& \sum_m \sum_n \sum_{t_a} \sum_a \sum_l Qhrv^s_{mnt_al} * chrv_{mnl} \\
& + \sum_m \sum_n \sum_{t_a} \sum_a \sum_l \sum_i \sum_r Qli^s_{mnt_alir} * (ftli_{mnli} + (vtli_{mnli} * d_{li})) \\
& + \sum_m \sum_n \sum_{t_a} \sum_a \sum_l \sum_r Qstr^s_{mnt_air} * cstr_{mnir} \\
& + \sum_m \sum_n \sum_{t_a} \sum_a \sum_i \sum_r \sum_k \sum_b Qik^s_{mnt_airkb} \times (ftik_{mnik} + (vtik_{mnik} * d_{ik})) \\
& + \sum_k \sum_b \sum_{t_a} \sum_a et^s_{t_abk} * vc_{kbt_a}])
\end{aligned} \qquad (3)$$

According to Equation 1, SC are the first-stage decision costs including investment and fixed operation and maintenance (O&M) costs to construct a power plant and $\sum_s (pr^s * TC^s)$ is the second-stage decisions (weighted tactical

Second-stage dtactical constraints are including.

$$Qhrv^s_{mnt_al} \leq j^s_{smnlt_a}$$

$$\forall S \in s, T_a \in t_a, A \in a, L \in l, M \in m, N \in n \qquad (9)$$

Equation 9 describes, all harvested volumes of materials, in each type and form, should be less or equal to the maximum available resource in that scenario, land, stage, and month.

$$\sum_m \sum_n \sum_l Qli^s_{mnt_alir} * \theta_{mn} + \sum_m \sum_n Qsrt^s_{mnt_a-1ir} - \sum_m \sum_n \sum_k \sum_b Qik^s_{mnt_airkb} \leq cap^{str}_{irt_a} * xi_{ir}$$

$$\forall S \in s, T_a \in t_a, A \in a, I \in i, R \in r$$

(10)

$$et^s_{t_abk} \leq cap^p_{kbt_a} * xk_{kb}$$

$$\forall S \in s, T_a \in t_a, A \in a, B \in b, K \in k$$

(11)

Equations 10 and 11 explain the capacity limitations of storage and power plant under establishment considerations.

$$\sum_l Qli^s_{mnt_alir} * \theta_{mn} + Qsrt^s_{mnt-1_air} = \sum_k \sum_b Qik^s_{mnt_airkb} + Qsrt^s_{mnt_air}$$

$$\forall S \in s, T_a \in t_a, A \in a, I \in i, R \in r, M \in m, N \in n$$

(12)

$$et^s_{t_abk} = \sum_m \sum_n \sum_i \sum_r (Qik^s_{mnt_airkb} * ev_{mnt_a}) * eff_{kb}$$

$$\forall S \in s, T_a \in t_a, A \in a, B \in b, K \in k$$

(13)

$$et^s_{t_abk} = \sum_v ed^s_{t_abkv}$$

$$\forall S \in s, T_a \in t_a, A \in a, B \in b, K \in k$$

(14)

Equation 12, 13, and 14 are balance constraints to show equality between input and output in the storage and power plant.

$$\sum_m \sum_n Qsrt^s_{mnt_air} \geq \beta_{t_a} * \sum_m \sum_n \sum_k \sum_b Qik^s_{mnt_airkb}$$

$$\forall S \in s, T_a \in t_a, A \in a, I \in i, R \in r$$

(15)

Equation 15 demonstrates the storage should maintain the safety stock in each period to deal with the uncertainty of available material in the future.

$$\sum_k \sum_b ed^s_{t_abkv} = cl_{vt_a} \quad \forall S \in s, T_a \in t_a, A \in a, V \in v$$

(16)

Equation 16 explains that total distributed electricity should satisfy the demand of consumers.

DSR constraints are including

$$DSR^s_{t_a} \geq (SC + TC^s) - \omega \quad \forall S \in s, T_a \in t_a$$

(17)

$$\sum_s \sum_{t_a} pr^s * \left(DSR^s_{t_a}\right) \leq R$$

(18)

Equations 17 and 18 describe the upper and lower bound of *DSR*. The parameter R is the maximum acceptable level of DSR that is the highest risk level for investors. ω is an ideal target that investors are willing to the realization of it, after the disaster.

As before discussed, we have assumed ω is the optimal PrSCC under routine uncertainties. It is known as the ideal value for stakeholders that it justifies the investment. In another word, investors will be satisfied if the costs of the supply chain after the occurrence of disaster has the minimum gap with the costs over the predisaster stage (under routine uncertainties). Accordingly, to calculate ω, we should optimize the PrSCC. In this regard, a nondeterministic mathematical model is developed under routine uncertainties to calculate decision costs without considering scenario and substage sets.

Equation (19) describes *PrSCC* objective function as bellow:

$$MinPrSCC = SC + TC$$

(19)

where *SC* follows Equation 5 and *TC* is

$$TC = \sum_m \sum_n \sum_t \sum_l Qhrv_{mntl} * chrv_{mnl} + \sum_m \sum_n \sum_t \sum_l \sum_i \sum_r Qli_{mntlir}$$

$$\times \left(ftli_{mnli} + (vtli_{mnli} * d_{li}) + \sum_m \sum_n \sum_t \sum_i \sum_r Qstr_{mntir} * cstr_{mnir}\right.$$

$$+ \sum_m \sum_n \sum_t \sum_i \sum_r \sum_k \sum_b Qik_{mntirkb} * \left(ftik_{mnik} + (vtik_{mnik} * d_{ik})\right)$$

$$\left. + \sum_k \sum_b \sum_t et_{tbk} * vc_{kbt} \right.$$

(20)

Subject to:

Equations 7 to 18 (without indexes s and a).   (21)

The configuration of the *PrSCC* model under routine conditions is completely similar to the *PoSCC* model with this difference that disruption scenarios, separated main, and substages do not exist in the structure of formulas. In another word, the space of decision-making is integrated and it is not decomposed.

It means the behaviors of uncertain parameters (material availability, material quality, and electrical demand) are proportional to defined statistical distribution func-

$$\text{Total CTP tactical costs}^s = \sum_m \sum_n \sum_{t_a} \sum_a \sum_l Qhrv^s_{mnt_al} * ehrv_{mnl}$$
$$+ \sum_m \sum_n \sum_{t_a} \sum_a \sum_l \sum_i \sum_r Qli^s_{mnt_alir} * \left(feli_{mnli} + \left(veli_{mnli} * d_{li} \right) \right)$$
$$+ \sum_m \sum_n \sum_{t_a} \sum_a \sum_i \sum_r \sum_k \sum_b Qik^s_{mnt_airkb} * \left(feik_{mnik} + \left(veik_{mnik} * d_{ik} \right) \right)$$
$$+ \sum_k \sum_b \sum_{t_a} \sum_a et^s_{t_abk} * ecnv_{kb}] * etax$$
   (23)

tions and disruption scenarios do not affect their probability function's characteristics. Therefore, we can consider Equations 7 to 18 as the constraints of the PrSCC model with ignoring indexes s and a and considering an integrated time set, $t = \{1 \dots T\}$. After calculating the optimal costs of the PrSCC model, it will be replaced as the ω in Equation 17 of the *PoSCC* model. The presented two-stage model in this chapter is the main configuration of a cost minimization model for constructing a bioenergy supply chain under disruptive uncertainties and DSR considerations. In the following, the effect of CMPs on the model structures has been discussed.

4 | CMP FORMULATIONS

In this part, different CMPs approaches according to the CTP, COP, and CCS add to the body of the *PoSCC* model. Due to introduced parameters, first, the CR models are formulated (PoSCC-CTP, PoSCC-COP), and then, the CCS-based model is presented (PoSCC-CCS).

4.1 | PoSCC-CTP model

Carbon tax as an environmental policy imposes the financial penalty for the released CO_2 to different layers of the supply chain. The penalty costs add to the objective function as new cost elements. This policy does not allocate any capacity limitation on carbon emission. The formulated objective function of this policy is as below:

$$\text{Min } PoSCC-\text{CTP}$$
$$= SC + [\sum_s pr^s * (TC^s + \text{Total CTP tactical costs}^s)]$$
   (22)

where SC and TC^s follow the Equations 5 and 6 and

Subject to:

Equations 7 to 18

The objective function under CTP considerations (Equation 22) has additional components compared with *PoSCC* model (Equation 4), which it refers to the penalty costs of CO_2 emission over supply chain operations (Equation 23).

4.2 | PoSCC-COP model

Carbon offset as an environmental regulation allocates a limited capacity to CO_2 emission through supply chain operations. However, purchasing the additional carbon capacity from the market is permitted. In another word, the required surplus capacity can be supplied; nevertheless, unused carbon capacity cannot be sold.

If $spc^s_{t_a}$ would be a variable to show the amounts of surpluses purchased carbon capacity and Cap_{t_a} would be the permitted emission capacity in the stage a and time t_a, the objective function and related constraint to this policy are presented as below:

$$\text{Min PoSCC - COP} = SC + \left[\sum_s pr^s * (TC^s + \text{Total COP tactical costs}^s) \right]$$
   (24)

where SC and TC^s follow the Equations 5 and 6 and

$$\text{Total COP tactical costs}^s = \sum_{t_a} \sum_{a} cp * spc^s_{t_a a} \quad (25)$$

Subject to:

Equations 7-18

And

$$
\begin{aligned}
\text{PoSCC} - \text{COP Constraint} = \Bigg[&\sum_{m} \sum_{n} \sum_{t_a} \sum_{a} \sum_{l} Qhrv^s_{mnt_a l} * ehrv_{mnl} \\
&+ \sum_{m} \sum_{n} \sum_{t_a} \sum_{a} \sum_{l} \sum_{i} \sum_{r} Qli^s_{mnt_a lir} * \left(feli_{mnli} + \left(veli_{mnli} * d_{li} \right) \right) \\
&+ \sum_{m} \sum_{n} \sum_{t_a} \sum_{a} \sum_{i} \sum_{r} \sum_{k} \sum_{b} Qik^s_{mnt_a irkb} * \left(feik_{mnik} + (veik_{mnik} * d_{ik}) \right) \\
&+ \sum_{k} \sum_{b} \sum_{t_a} \sum_{a} et^s_{t_a bk} ecnv_{kb} \Bigg] \leq Cap_{t_a} + spc^s_{t_a} S \in s, T_a \in t_a, A \in a
\end{aligned}
\quad (26)
$$

According to Equation 24, the costs of purchasing new carbon capacity add to the objective function while the total carbon emission over supply chain operations should not excess permitted capacity (Equation 26).

4.3 | PCC-CCS model

CSS technology is one of the options to implement the TI approach for dealing with carbon emission. To impose CCS regulation on the model, the main structure othe supply chain should be connected to the set of facilities and operations which are involved in capturing, transportation, and store the carbon underground. The related mathematical elements to connect CCS structure to the main model are described in continue.

The presented objective function under CCS regulation is a combination of two supply chain elements related to the bioenergy generation and CCS network structures. Therefore, the investment and operational costs of both are considered in the model. All the strategic and tactical decisions of structuring a CCS network are considered and added to the model. Decisions for selecting the best locations and sizes to establish capture unit, geological storage, and pipeline facility between capture unit and storage are considered as the strategic decisions and tactical decisions considering flows of transformed and stored CO_2 through the CCS network. In this regard, the PoSCC-CCS model is formulated as below:

$$
\begin{aligned}
\text{Min PoSCC - CCS} = &SC + \text{Total CCS establishment costs} \\
&+ \left[\sum_{s} pr^s * (TC^s + \text{Total CCS tactical costs}^s) \right]
\end{aligned}
\quad (27)
$$

where SC. and TC^s follow the Equations 5 and 6 and

Total CCS establishment costs

$$
\begin{aligned}
= &\sum_{y} \sum_{q} \left[isc_{yq} + fsc_{yq} \right] * x_{yq} \\
&+ \sum_{j} \sum_{q} \sum_{h} \left[ipj_{jqh} + fpj_{jqh} \right] * x_{jqh} \\
&+ \sum_{u} \sum_{h} \left[igs_{uh} + fgs_{uh} \right] * x_{uh}
\end{aligned}
\quad (28)
$$

And

Total CCS tactical costs^s

$$
\begin{aligned}
= &\sum_{y} \sum_{q} \sum_{t_a} \sum_{a} \sum_{b} \sum_{k} Csc^s_{yqbkt_a} * cc_{yq} \\
&+ \sum_{j} \sum_{t_a} \sum_{a} \sum_{q} \sum_{h} \sum_{u} \sum_{h} Ctp^s_{jt_a yquh} * \left(ftp_{jqh} + (vtp_{jqh} * d_{qh}) \right) \\
&+ \sum_{t_a} \sum_{a} \sum_{u} \sum_{h} Csg^s_{t_a uh} * hg_{t_a uh}
\end{aligned}
\quad (29)
$$

According to Equations 27-29, the objective function of the PoSCC-CCS model has several new components depending on the investment and fixed O&M costs to establish a capture unit, pipeline, and geological storage. The added tactical costs are including carbon capturing, transferring, and storage costs through the CCS operations. The PoSCC-CCS model not only includes the previous constraints (Equations 7-18) but also contains new limitations as below:

$$
\sum_{k} \sum_{b} Csc^s_{yqbkt_{a}} = \sum_{k} \sum_{b} (et_{t_a bk} * ecnv_{kb}) * eff_{yq}
\quad (30)
$$
$$\forall S \in s, T_a \in t_a, A \in a, Y \in y, Q \in q$$

Equation 30 shows the amount of captured CO_2 is dependent on the generated electricity, emission rate, and efficiency of the capture unit.

$$
\sum_{k} \sum_{b} Csc^s_{yqbkt_a} \leq cap^{cap}_{yq} * x_{yq}
$$
$$\forall S \in s, T_a \in t_a, A \in a, Y \in y, Q \in q \quad (31)$$

Equation 31 describes that the amounts of captured CO_2 should be less or equal to the capacity of the capture unit.

$$Ctp^s_{jt_ayquh} = Csc^s_{yqt_a} * eff_{jqh}$$

$$\forall S \in s, T_a \in t_a, A \in a, U \in u, h \in H, J \in j, Y \in y, Q \in q. \quad (32)$$

$$Csg^s_{t_auh} = \sum_j \sum_y \sum_q Ctp^s_{jt_ayquh} * eff_{uh}$$

$$\forall S \in s, T_a \in t_a, A \in a, H \in h, U \in u \quad (33)$$

Equations 32 and 33 describe that the amounts of transported and stored carbon by pipeline and geological storage are equal to the input carbon and efficiency of facilities.

$$Ctp^s_{jt_ayquh} \leq cap^{pip}_j * x_{jqh}$$

$$\forall S \in s, T_a \in t_a, A \in a, Q \in q, H \in h, J \in j, Y \in y, U \in u \quad (34)$$

$$Csg^s_{t_auh} + Csg^s_{t-1_auh} \leq cap^{gs}_{uh} * x_{uh}$$

$$\forall S \in s, T_a \in t_a, A \in a, U \in u, H \in h \quad (35)$$

Equations 34 and 35 address the capacity limitations of received carbon by the pipeline and storage.

$$\sum_u \sum_h Csg^s_{t_auh} = tcs_{t_a} \quad \forall S \in s, T_a \in t_a, A \in a \quad (36)$$

Equations 36 emphasizes that the amounts of stored carbon in geological storage should be equaled to the defined target value to mitigate and store carbon underground.

$$\sum_y \sum_q x_{yq} \leq B_1 \quad (37)$$

$$\sum_u \sum_h x_{uh} \leq B_2 \quad (38)$$

$$\sum_j x_{jqh} \leq 1 \quad (39)$$

$$\forall Q \in q, H \in h$$

Equations 37 and 38 describe that the established capturing units and geological storages should be less or equal to the permitted numbers (B_1 and B_2). Equation 39 emphasizes that between every two points of the capture unit and geological storage just one size of the pipeline facility could be selected.

All provided CPM-based models are trying to describe the changes in the basic PoSCC model under environmental considerations. With ignore of scenario set s, and substage set

a, as well as integrating the time horizon of the problem in the form of $t = \{1 \dots .T\}$, the PrSCC-CTP, PrSCC-COP, and PrSCC-CCS models can be formulated similarly.

To analyze the performance of the formulated models and CMP scenarios, in the next chapter, the Mississippi case study is presented and discussed.

5 | NUMERICAL RESULTS

5.1 | Case study

Mississippi, as one of the southern states of the United States, due to 305,010,178 hectares of forests, is known as a high potential area for forest wood extraction and utilization in bioenergy and biofuel generation. Opportunities for biofuel and bioelectricity generation in this state have been subjects of several studies in recent years.[54]

The majority of forestlands in this state are covered with pine and hardwood, which often found in two shapes of pulpwood and saw timber.[54] Although this state has great access to forest resources, natural disasters have always been serious threats to forest conservation, availability of wood resources, the stability of the timber market, and the quality of wood materials. For instance, the Katrina hurricane in August 2005 led to intensive damages to the forests in the forms of lean or blowdown.[55,56] Although this destructive cyclone affected a large part of the Mississippi State, the 15 counties in the southeast area suffered the most. Figure 3 shows the level of damage in the 6 most destructed southeast counties of Mississippi after the Katrina hurricane.

Details of pine pulpwood, pine saw timber, hardwood pulpwood, and hardwood saw timber types for all 15 counties in the southeast of Mississippi are in Appendix A. These volumes are the monthly average materials that are available in the routine condition.

To perform the effects of routine uncertainty, for instance, seasonal changes and climatic variations, $\pm 10\%$ fluctuations are considered in the average available forest biomass in each county. It is assumed that the monthly average volumes for each county in the routine condition are distributed by Uniform distribution function in an interval with minimum and maximum boundaries as below.

$$\text{Forest availability} = \text{Uniform (Minimum value, Maximum value)} \quad (40)$$

where

$$\text{Minimum value} = \text{average value - average value} * (0.10) \quad (41)$$

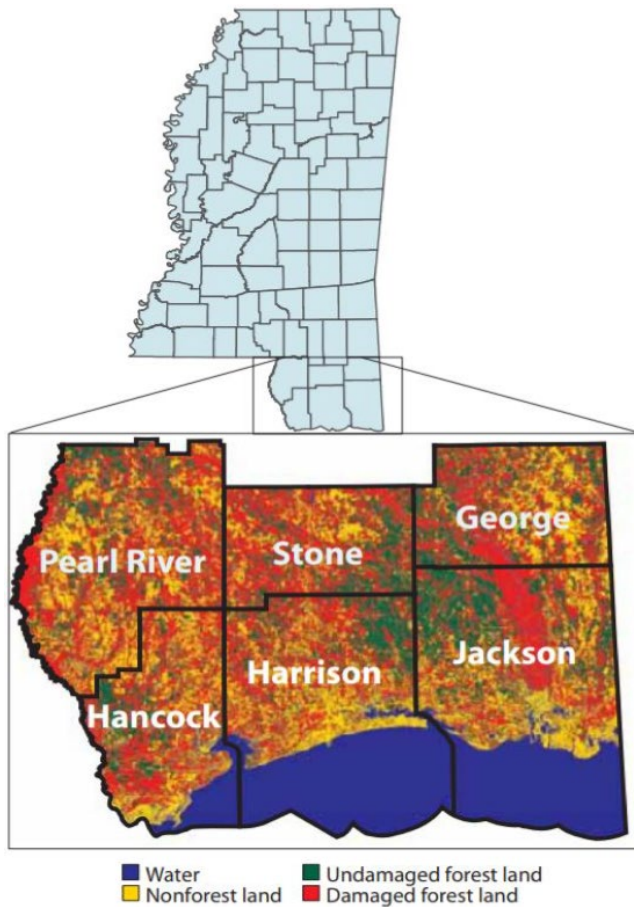$$\text{Maximum value} = \text{average value} + \text{average value} * (0.10) \quad (42)$$

FIGURE 3 General view of frost damage by Hurricane Katrina[57]

After the natural disaster, the Katrina hurricane, the fluctuations in the forest availability are changed significantly. According to the reports,[57] the consequences of the Katrina hurricane caused 15-30% fluctuations in the blowdown factor, as the most prevalent factor, in several counties.

Hence, to consider the impact of disruption in the availability of the forest, four scenarios with −15, −20, −25, and −30% reductions of greenwood resources are applied to the model. The loss of material is assumed to be zero, hence during the damage substage, the amount of salvaged resources after the disaster are equal to initial resources minus reduced green material under each scenario.

Obviously, the quality of green and salvaged woods is wieldy depend on the weather conditions and levels of the damage. Shabani[58] presented an equation to measure the energy value (EV) of green materials regarding the MC and HHV values (Equation 43). We have generalized this formula to each time, type, and form of green resources.

$$EV_{mnt_a} = HHV_{mnt_a} * \left(1 - MC_{mnt_a}\right)$$
$$\forall M \in m, N \in n \tag{43}$$

According to the Haliwood and Horrobin's theory, the MC of woody material can be calculated depending on several indicators such as air temperature, humidity, and molecular weight of polymer unit that forms a hydrate in each time period.[59] In another study, the humidity factor is addressed as a parameter-dependent to the dew point and normal temperatures. The temperature is not a fixed parameter and it is usually fluctuating over time.[60] Therefore, the mentioned effective indicators obtain various values in each month.

In this way, Saghaei et al[61] have provided the effects of weather factors on the EV of forest biomass in a case study in the Mississippi State. According to this study, for better estimation, the upper and lower values of monthly dew point and normal temperatures have been pasted on the Haliwood and Horrobin's equations to calculate the forest biomass's MC. The minimum and maximum monthly dew point and normal temperatures are extracted from the online websites for each county. Consequently, the upper and lower boundaries of MC in each month are achieved (Appendix C).

Proportional HHV values are measured according to a general classification presented in Table 1 and employing the linear interpolation technique. Appendix C addresses the lower and upper boundaries of the MC, HHV, and EV in each month. The final EV value is chosen using a random selection in the uniform distributed intervals, with attention to the lower and upper bounds of EV.

In another side measuring the quality of the salvaged woods is a challenge, since it depends on different features such as the severity of the damage, timber decay, and environmental condition after a disaster.[62] To simplify it, Equation 44 is proposed to convert the quantities of green resources to salvaged type by multiplying to the specific parameter.[63]

$$Q_G^s = Q_{Sl}^s * K^{-1} \tag{44}$$

where the Q_G^s and Q_{Sl}^s are quantities of green and salvaged woods respectively, and K is a translate factor to convert the salvaged wood value to green type. In another word, the translate factor K explains the equivalent green quantitates of salvaged wood. Using this factor, we convert the salvaged resources to green type and then use the measured green EV values for them.

TABLE 1 HHV level of woody biomass based on MC percentage[71]

Moisture content (Wet basis %)	HHV (MWh)
0	5.65
20	4.52
50	2.82
80	1.13

HHV, higher heating value; MC, moisture content.

The average values for K after Hugo hurricane are reported as $K = 4.5$ and $K = 6.6$ for saw timber and pulpwood forms of pine, respectively.[64] Due to the lake of knowledge about relevant hardwood translate factors in these two forms (pulpwood and saw timber); in this study, reported values are generalized to hardwood forms too.

To consider postdisaster substages in our study, the first year after the disaster is introduced as damage stage when salvaged woods are available to supply instead of greenwoods. The second year addresses the recovery stage, when the green woods are recovered but it does not completely. In this regard, a random value between 10 and 15 percent is considered as the rate of greenwood unavailability over the recovery stage, in comparison with the predisaster phase. Finally, the last stage, as the back to sustainability, is performed with 0 to 10% material fluctuation.

The distribution of electrical demand for the southeast area of Mississippi after the Katrina hurricane is not exactly available. Generally, when the actual data are not available, the normal distribution function can be used to cover many information deficiencies of the system.[65] In this study, we have employed simulated data of monthly electricity consumption in the southeast area of Mississippi that is provided by[61] (Table 2).

Investment and fixed annual costs to establish facilities such as power plant and capture units are relevant to the size of these facilities. On the other side, the variable cost of the system is directly dependent on the electrical demand and stored materials. In this regard, the provided data by[61] are employed to consider efficiency, investment, fixed, and variable O&M costs and suggested sizes including 116, 119, and 122 MW to establish a power plant.

The storage capacity should be proportional to the electrical consumer demand (suggested sizes for power plant) and

TABLE 3 Storage capacity (m^3) for each power plant size

Power plant size (MW)[61]	Efficiency factor (%)[61]	Storage capacity (Dt)
116	30	347,198
119	35	309,105
122	40	273,867

the quality of materials. The storage capacity is proportional to the volumes of safety stock and required materials during routine conditions. It also should be as much as enough, for supporting of sudden increment in the material volumes, when the green resources are scarce and salvaged types with lower quality (higher quantities) should be replaced. In this regard, the storage capacity is suggested to be in proportion to the volumes of the dry material considering average EV of 4.5 (MWh/ Dry ton (Dt)), and average translate factor K of 5.5, with attention to all types and forms of materials. The storage capacity should be enough to run the power plant's operations for 20 days,[66] regarding the three mentioned sizes (Table 3).

Appendixes B and D address some of the other supply chain parameters and distance between locations. Given that, the location of the power plant in each county is defined as the distance from the forest resources. As we do not know the accurate amount of that, a numerical interval is proposed to calculate each county's distance from itself as a range between zero and root square mile of surface (S) in that county $(0, \sqrt{S}/2)$.

The CO_2 capturing unit size calculates in the proportion to the size of the power plant and electricity net generation. Appendix B introduces the costs and emission parameters of the CCS system, as the average values of the three

TABLE 2 Values of mean and SD for electricity consumption in each month/sector[61]

Monthly sector-based mean and SD of simulated electrical consumption (MWh)	Residential		Commercial		Industrial	
	Mean	SD	Mean	SD	Mean	SD
Jan	31,920	482.8	20,848	389.8	24,210	407.2
Feb	27,376	493.5	19,560	401.9	23,049	358.6
Mar	27,131	512.4	20,162	424.9	24,155	264.1
Apr	23,188	510.4	19,687	333.5	24,059	450.3
May	23,051	323.6	21,117	364.6	25,405	567.4
Jun	28,556	521.6	22,828	510.2	25,906	484.7
Jul	34,836	721.9	24,775	587.2	26,199	418.4
Aug	33,417	518.1	24,723	358.4	24,809	435.9
Sep	29,408	781.1	23,008	401.7	24,863	472
Oct	23,942	425.9	21,735	464.9	24,858	438.7
Nov	23,731	656.3	20,047	325.8	23,870	549
Dec	31,240	531.9	21,067	261.1	23,428	394.6

TABLE 4 Binary decisions (selected locations and sizes) and supplier counties in the predisaster stage

Decisions/ CMPs	CTP	COP	CCS
Material storage location	4 (Wayne)	4 (Wayne)	4 (Wayne)
Power plant location	4 (Wayne)	4 (Wayne)	4 (Wayne)
Capture unit location	4 (Wayne)	4 (Wayne)	4 (Wayne)
Geological storage location	4 (Wayne)	4 (Wayne)	4 (Wayne)
Material storage size (Dt)	273,867	273,867	273,867
Power plant size (MW)	122	122	122
Supplier counties*	4−3	4−3	4−3

CMPs, carbon mitigation policies; CTP, carbon tax policy; COP, carbon offset policy; CCS, carbon capture and storage.

*Appendix A.

implementable technologies for CCS including oxyfuel, precombustion, and postcombustion.[26] The provided information by Appendix B is converted data, proportional to the three suggested sizes for the power plant considering the scale factor 0.7 and US $ cost per unit.[67] The total CCS variable cost includes the CO_2 avoiding cost in the capture unit plus 10$ for transportation and storage.[68] Fixed O&M costs for total facilities of the CCS are assumed 3.5% of investment costs, similar to the power plant.[61]

The amount of CO_2 released during the CCS operations mainly depends on the emission of capturing unit, pipeline transferring process, and the associated underground carbon storage operations. To reduce carbon dioxide emissions and the cost of pipeline construction and decrease the risk of line failure, it is assumed that the CCS system is built in the same county where the power plant is established. The supply chain performance under CCS policy faces challenges such as the geographical conditions of the route between carbon storage and capture unit, and embedded facilities over carbon transferring and storage that may change the rate of carbon emissions. Thus, a random value between 5% and 10% is assumed for the CO_2 emission increment rate through transportation and storage operations. The CCS costs and emission are presented in Appendix B. The numerical results of the proposed model for the mentioned case study are widely presented in the next section.

6 | COMPUTATIONAL RESULTS

This section presents the computational results of the proposed models under several CMPs. GAMS software with a CPLEX solver has used to optimize mathematical models. Table 4 and Table 5 demonstrate the binary decisions and supplier counties under routine and disruptive uncertainties. The summation of realized monthly electricity consumption for three residential, commercial, and industrial sectors is provided in Figure 4. According to Figure 4, the most consumption rate refers to January with 85.9 thousand MWh. Among the three suggested sizes to establish power plants, 122 MW has been the best size to cover the electricity demand completely in both routine and disruptive conditions.

Over the predisaster stage, county 4 (Wayne) has been selected as the best place to establish the power plant. Regarding the transportation cost concept, the same county is proposed as the best location to establish the material storage and CCS facility.

Over the postdisaster stage, the best location to establish facilities is changed to the country 7 (Forrest). Values of harvested materials in two forms of salvaged and greenwood are equaled for all CMPs. However, according to the dramatic decrement in the availability of green woods, the required material is supplied from a wider range of counties (Table 5).

TABLE 5 Binary decisions (selected locations and sizes) and supplier counties in the postdisaster stage

Decisions/ CMPs	CTP	COP	CCS
Material storage location	7 (Forrest)	7 (Forrest)	7 (Forrest)
Power plant location	7 (Forrest)	7 (Forrest)	7 (Forrest)
Capture unit location	7 (Forrest)	7 (Forrest)	7 (Forrest)
Geological storage location	7 (Forrest)	7 (Forrest)	7 (Forrest)
Material storage size (Dt)	273,867	273,867	273,867
Power plant size (MW)	122	122	122
Supplier counties*	1-2-3-4-5-6-7-8-9-11-12	1-2-3-4-5-6-7-8-9-11-12	1-2-3-4-5-6-7-8-9-11-12

CMPs, carbon mitigation policies; CTP, carbon tax policy; COP, carbon offset policy; CCS, carbon capture and storage.
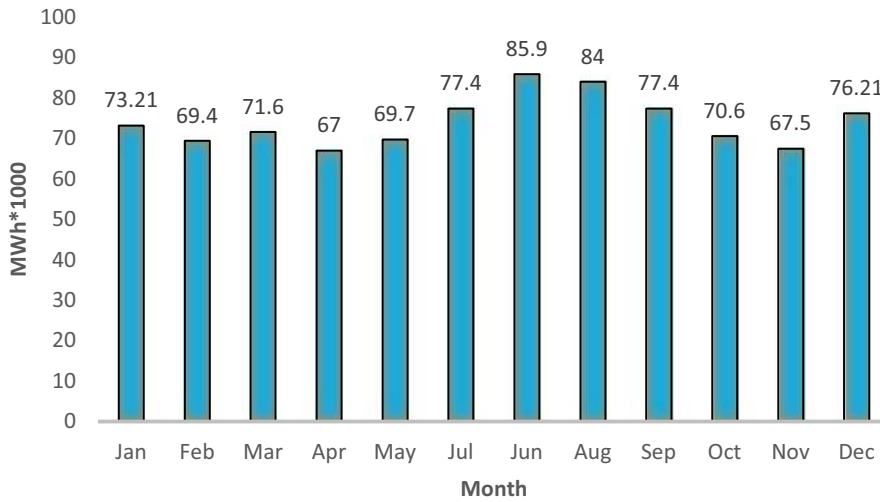
*Appendix A.
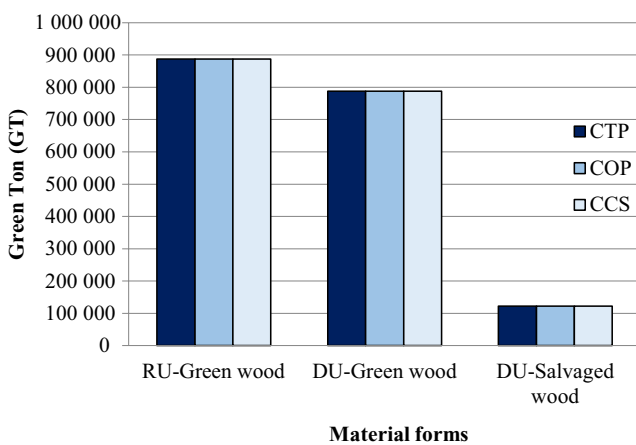
FIGURE 5 Total supplied materials under routine and disruptive uncertainties

FIGURE 6 The green materials contributions under RU
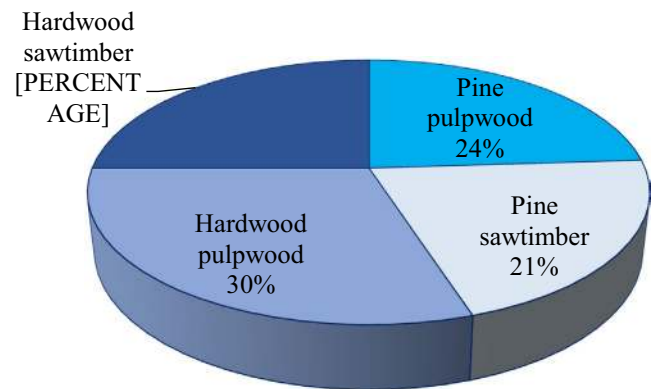
FIGURE 7 The green materials contributions under DU

Figure 5 shows the total supplied materials in two forms of green and salvage over both pre- and postdisaster stages. The salvaged materials are available exclusively in the postdisaster stage.

The total supplied green material under routine (ru) and disruptive uncertainties (DU) is 887,634 and 787,566 Green ton (Gt), respectively. At the same time, the volumes of salvaged material under disruption have been 122,371.9 Gt. According to Figure 5, there is not any considerable gap in the total supplied green materials between RU and DU. However, the contribution of material based on their types and forms is different. In this way, Figures 6, 7,and demonstrate the proportions of pine pulpwood, pine saw timber, hardwood pulpwood, and hardwood saw timber for both forms of green and salvaged woods. Over the routine conditions (predisaster stage), pine pulpwood with the 48% contribution has the most share regarding the higher resource availability in comparison with others (Figure 6). Due to the significant depletion of resources under disruptive conditions, the percentage of resource utilization has been adjusted and the participation

of other types of resources is increased. However, the 24% reduction in the volume of pine pulpwood under disruption (Figure 7) leads to the 80% contribution of salvaged wood (Figure 8).

The difference in the numbers and locations of suppliers and the volumes of supplied materials under RU and DU affect the operational and environmental performance of the supply chain considering CMPs. Figure 9 shows the costs of
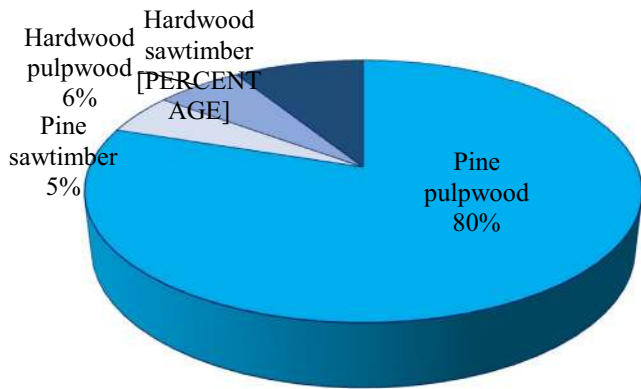
FIGURE 8 The salvaged materials contributions under DU
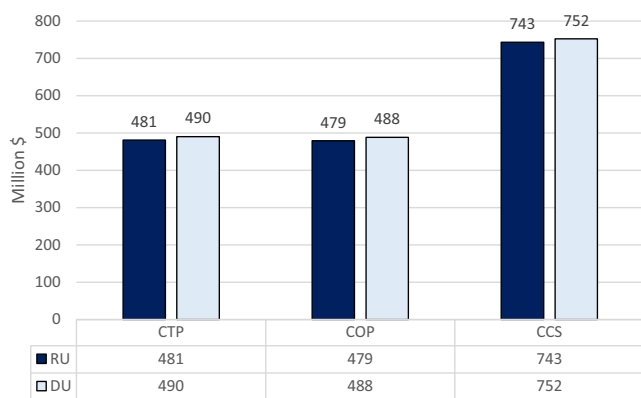
FIGURE 9 The total costs of bioenergy supply chain affected by RU, DU, and several CMPs

implementing a bioelectricity supply chain under CMPs for both routine and disruptive conditions.

The presented costs in Figure 9 are the first-year PoSCC results including investment costs, fixed and variable O&M costs, and operational and environmental costs under CMPs. Tables 6-9 present details of them. As before discussed, to run the PoSCC model, we need to determine the parameter ω as the optimal PrSCC. In this regard firstly, we have calculated the optimal costs of the bioenergy supply chain under RU considering CMPs. The detailed cost elements for the predisaster model are presented in Table 6.

In continue, the cost elements of the supply chain in the postdisaster stage are presented under each CMPs separately considering disruption scenarios (Tables 7-9). Finally, Figure 10 demonstrates the amounts of DSR for each CMP with attention to the provided information.

Tables 7-9 illustrate supply chain cost items under disruption scenarios including 15, 20, 25, and 30% reduction in primary resources (chapter 5). According to Table 6, operational cost elements for all CMPs have equal values. This is because the reported data are the minimum required costs to operate the power plants and fulfill consumer demand. The most and least objective function values refer to CCS and COP, respectively. As well as, in the COP and CTP scenarios, there are environmental costs related to the purchased surplus carbon capacity and the tax imposed on the emission.

Similarly, Tables 7-9 show the cost elements of the postdisaster model under disruptive uncertainty. The same as the predisaster model, COP, and CCS have the best and worst economic results, respectively. The behavior of each scenario

TABLE 6 Table Numerical results of annually PrSCC under CMPs

Costs($)/CMPs	CTP	COP	CCS
Total Investment cost ($)	441,854,606	441,854,606	687,694,838
Total Fixed O&M cost ($)	16,790,475	16,790,475	25,470,686
Material harvesting cost ($)	8,254,998	8,254,998	8,254,998
Material transportation cost from l to i ($)	5,516,730	5,516,730	5,516,730
Material transportation cost from i to k ($)	2,435,070	2,435,070	2,435,070
Material storage cost ($)	875,971	875,971	875,971
Electricity generation cost ($)	3,797,034	3,797,034	3,797,034
Purchase surplus carbon cost ($)	–	115,237	–
CO_2 emission cost over harvesting ($)	159,774	–	–
CO_2 emission cost over transportation from l to i ($)	7,020	–	–
CO_2 emission cost over transportation from i to k ($)	1,797	–	–
CO_2 emission cost over material storing ($)	22,775	–	–
CO_2 emission cost over electricity generation ($)	1,460,741	–	–
Total CCS operational cost ($)	–	–	9,361,593
Total ($)	481,176,991	479,640,121	743,406,920

CMPs, carbon mitigation policies; CTP, carbon tax policy; COP, carbon offset policy; CCS, carbon capture and storage; PrSCC, predisaster supply chain cost.

TABLE 7 Numerical results of first-year PoSCC under COP and disruptive scenarios

Costs($)/CMPs	S_1	S_2	S_3	S_4	Two-stage model
Investment cost ($)	441,854,606	441,854,606	441,854,606	441,854,606	441,854,606
Fixed O&M cost ($)	16,790,475	16,790,475	16,790,475	16,790,475	16,790,475
Material harvesting cost ($)	11,679,860	11,689,000	11,654,910	11,660,840	11,671,153
Material transportation cost from l to i ($)	9,130,891	9,036,998	8,883,622	8,884,112	8,983,906
Material transportation cost from i to k ($)	3,507,711	3,502,472	3,501,701	3,504,423	3,504,077
Material storage cost ($)	1,771,496	1,754,998	1,754,892	1,779,034	1,765,105
Electricity generation cost ($)	3,797,034	3,797,034	3,797,034	3,797,034	3,797,034
Purchase surplus carbon cost ($)	138,041	138,103	138,105	138,155	138,101
Total ($)	488,670,114	488,563,686	488,375,345	488,408,679	488,504,457

CMPs, carbon mitigation policies; COP, carbon offset policy; PoSCC, postdisaster supply chain costs.

TABLE 8 Numerical results of first-year PoSCC under CCS and disruptive scenarios

Costs($)/CMPs	S_1	S_2	S_3	S_4	Two-stage model
Total Investment cost ($)	687,694,838	687,694,838	687,694,838	687,694,838	687,694,838
Total Fixed O&M cost ($)	25,470,686	25,470,686	25,470,686	25,470,686	25,470,686
Material harvesting cost ($)	11,679,860	11,658,570	11,654,991	11,660,840	11,663,565
Material transportation cost from l to i ($)	9,130,891	9,045,902	8,883,622	8,884,112	8,986,131.8
Material transportation cost from i to k ($)	3,507,711	3,502,349	3,701,701	3,504,423	3,554,046
Material storage cost ($)	1,771,493	1,746,752	1,754,892	1,779,187	1,763,081
Electricity generation cost ($)	3,797,034	3,797,034	3,797,034	3,797,034	3,797,034
Total CCS operational cost ($)	9,361,593	9,361,593	9,361,593	9,361,593	9,361,593
Total($)	752,414,106	752,277,724	752,319,357	752,152,713	752,290,975

CMPs, carbon mitigation policies; CCS, carbon capture and storage; PoSCC, postdisaster supply chain costs.

refers to the ratios of available salvaged wood compared with greenwood.

In scenario 1, the availability of salvaged material is not considerable, as results, due to the shortage of salvaged wood and the needs of the system to be fed; some cost elements have increased to supply green resources from a wider range of counties. In scenarios 2 and 3 although green wood reduction rate is higher than scenario 1; however, rate of replacing salvaged wood is more than it; consequently, the system can reduce the needs of harvesting material from farther counties. As discussed, increasing and decreasing costs of the supply chain in exchange for parametric volatility have been achieved by efforts to minimize costs and maximize DSR reduction. In this regard, Figure, 10 shows the amounts of DSR under CMPs separately.

As in Figure 10, the highest DSR belongs to CTP, which has the most cost increment over the postdisaster stage. It is because of the allocated carbon tax to the whole operations of the supply chain. It means the role of disruption on the

material availability rate has more effect on the rate of emission that is deserving to penalty costs, in comparison with the shortage of carbon capacity (COP) or volumes of transferred carbon (CCS).

Another important issue is the green material proportion in comparison with the salvaged type in each scenario and its effects on the DSR. As it is observable, all three CPMs have experienced the highest DSR under scenario 1. This scenario assumes the least amount of destruction in the primary sources. However, the reduced availability of green materials, along with limit accessory to salvaged resources (compared to other scenarios), has made the supply chain obliged to supply green materials from farther counties. It has led to an increase in the cost of material shipping.

To evaluate the level of problem complexity under routine and disruptive conditions, considering CMPs, we have analyzed the solving time for different sizes of the problem. The analyzed sizes and results are presented in Table 10.
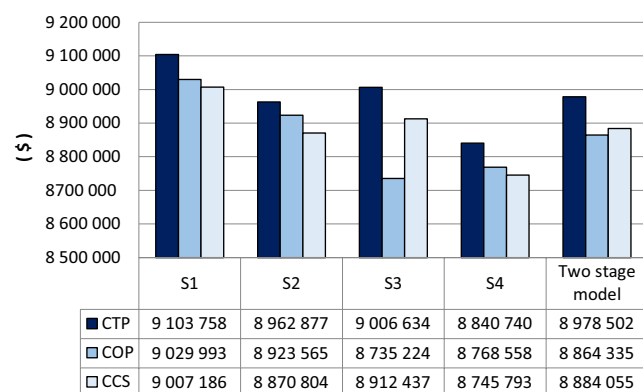
TABLE 9　Numerical results of first-year PoSCC under CTP and disruptive scenarios

Costs($)/CMPs	S_1	S_2	S_3	S_4	Two-stage model
Investment cost ($)	441,854,606	441,854,606	441,854,606	441,854,606	441,854,606
Fixed O&M cost ($)	16,790,475	16,790,475	16,790,475	16,790,475	16,790,475
Material harvesting cost ($)	11,679,860	11,658,570	11,654,991	11,660,840	11,663,565
Material transportation cost from l to i ($)	9,130,891	9,045,902	8,883,622	8,884,112	8,986,132
Material transportation cost from i to k ($)	3,507,711	3,502,349	3,701,701	3,504,423	3,554,046
Material storage cost ($)	1,771,493	1,746,752	1,754,892	1,779,187	1,763,081
Electricity generation cost ($)	3,797,034	3,797,034	3,797,034	3,797,034	3,797,034
CO_2 emission cost over harvesting ($)	218,624	218,252	218,195	218,333	218,351
CO_2 emission cost over transportation from l to i ($)	19,746	16,268	18,237	18,216	18,116.75
CO_2 emission cost over transportation from i to k ($)	3,510	3,504	3,504	3,506	3,506
CO_2 emission cost over material storing ($)	46,058	45,415	45,627	46,258	45,839.5
CO_2 emission cost over electricity generation ($)	1,460,741	1,460,741	1,460,741	1,460,741	1,460,741
Total ($)	490,280,749	490,139,868	490,183,625	490,017,731	490,155,493

CMPs, carbon mitigation policies; CTP, carbon tax policy; PoSCC, postdisaster supply chain costs.

The size 1 refers to the presented case study, which includes 15 counties and indexes such as potential locations of forestlands (l), material storages (i), power plants (k), capture units (q), geological storages (h). The solving time of the predisaster model under CTP, COP, and CCS for size 1 has been 71, 54, and 112 seconds. Similarly, for the postdisaster model under disruptive scenarios, 90, 61, and 144 seconds are recorded, respectively.

By increasing the size of the problem from case 1 to 4, the gap of solving time between pre- and postdisaster is evaluated considering CMPs. The results show that by increasing the size of the problem, the solving time is increased. Noticeably, significant growth in solving time is observed in the CCS scenario with attention to the existence of more viables and parameters.

6.1 | Fancial analysis

Regarding DSR results and a considerable gap between CMP's economic performances in the pre- and postdisaster stages, financial analysis is employed based on the NPV concept to evaluate economical attractions of CMPs under disruptive conditions.

Net present value (NPV) in engineering economics is one of the standard methods of evaluating economic plans. In this way, the cash flow (income and expense) is discounted based on the time of occurrence (income or expense). Present net value is widely used in economic calculations, engineering economics, countries' budgets, microeconomics, macroeconomics, commerce, and industry. In this way, the NPV formulation is presented below:

$$NPV = \sum_t R_t / (1+i)^t. \tag{45}$$

FIGURE 10　The DSR values ($) under disruptive scenarios and CMPs considerations

	S1	S2	S3	S4	Two stage model
CTP	9 103 758	8 962 877	9 006 634	8 840 740	8 978 502
COP	9 029 993	8 923 565	8 735 224	8 768 558	8 864 335
CCS	9 007 186	8 870 804	8 912 437	8 745 793	8 884 055

TABLE 10　Gaps in solving time for postdisaster model compared with the predisaster model under several problem sizes and CMPs

Size of problem (l, i, k, q, h)/CMPs	CTP	COP	CCS
1 - (15,15,15,15,15)	27	14	29
2 - (21,22,1918,17)	27	14	30
3 - (25,27,23,22,26)	29	15	33
4 - (30,32,34,29,33)	32	20	37

CMPs, carbon mitigation policies; CTP, carbon tax policy; COP, carbon offset policy; CCS, carbon capture and storage.

where t is the period index, i is the internal rate of return (IRR), and R_t is the net cash outflow in the period. Obviously, at the beginning of the project, there is no revenue, and investment and fixed O&M costs are only the financial flow at the start point.

Economic comparison of projects is one of the important approaches that can affect investment attractiveness. Many investors face different conditions and investment options that can lead them to profitability or in contrast losing the opportunity.herefore, evaluating and comparing the economic performance of different projects would have a key role to justify stakeholders. There are various methods for economic comparinof p. However, IRR method offers a comprehensive approach to determining the interest rate of investment over time. The other advantage of using IRR is the opportunity of comparing it with the minimum attractive return rate (MARR). This comparison can result in selecting the best alternatives for investment. In addition, this method helps to find out how much opportunity is lost after investment in each project. To perform the *IRR*. approach, an equal investment payback period should be considered for all projects. Then, by using Equation 46, the *IRR*. is calculated for each plan where P. is the initial investment value, N. is the investment payback period, and a. is the net profit in each period.

$$NPV = -P + \frac{a_1}{(1+IRR)^1} + \frac{a_2}{(1+IRR)^2} + \ldots + \frac{a_N}{(1+IRR)^N} = 0.$$

(46)

If $IRR \geq MARR$, the plan has economic feasibility. Otherwise, it wod not be an attractive option for investment.

To compare plans, multiple cases are introduc.onsidering plans A. and B., three situations will be occurred as below:

1. Pns A. and B. have equal P. In this condition, the plan with hher *IRR*. is the best option for investment.
2. Plans A. and B. have equal *IRR*.; in this condition, the plan with lower P. is the best option for investment.
3. Plans A. and B are feasible; however, $P_A > P_B$ while $IRR_A < IRR_B$ in this condition if $\Delta IRRA - B \geq MARR$, then plan A would be selected as the best option. Otherwise, B would be a better economical alternative.

Ading to what was discussed, various CMPs are compared in terms oeconomic for determining the IRR of the project for each CMPs and its investment attractions. Compared projects are considered for after disaster conditions. To calculate NPV, t average electricity sale rate is considered 90.9 $ per MWh.[69] The time horizon after the disaster, as is discussed earlier, is divided into three stages including the first yr (damage stage), second year after the disaster (recovery stage), and the third year as the back to sustainability stage. The MARR is considered equal to the bank discount rate in the Mississippi (1.25% per annum).[70] In addition, the investment payback period is considered 40 years for each CMP. Table 11 shows the cost, revenue, and profit values. Items reported in Table 11 include investment costs, annual fixed O&M costs, and variable costs of each CPM (total costs of harvesting, transportation, storage, electricity generation, and environmental costs), which are listed in Tables 7, 8,9 and with details. These tables report only the costs associated with the first year. The costs of the system in the second and third years are then calculated based

TABLE 11 Financial analysis of CMPs after disruption

Costs($)/Scenarios	CTP	COP	CCS
Investment cost ($)	441,854,606	441,854,606	687,694,838
Fixed O&M cost ($) (Annually)	16,790,475	16,790,475	25,470,686
Total Variable cost($) (First year)	31,510,412	29,859,375	39,125,451
Total Variable cost($) (Second years)	29,692,261	28,136,489	36,867,912
Total Variable cost($) (Third year onwards)	22,511,410	20,995,040	30,241,396
Total Income($) (Annually)	80,893,728	80,893,728	80,893,728
Total profit($) (First year)	32,592,841	34,243,878	16,297,591
Total profit ($) (Second year)	34,410,992	35,966,764	18,555,130
Total profit ($) (Third year onwards)	41,591,843	43,108,213	25,181,646
Investment payback period (Year)	40	40	40

CMPs, carbon mitigation policies; CTP, carbon tax policy; COP, carbon offset policy; CCS, carbon capture and storage.

TABLE 12 Financial analysis of project under different CMPs

Items/Plans	CTP	COP	CCS
MARR (%)	1.25	1.25	1.25
IRR (%)	9	9	2
Feasibility	yes	yes	yes
Missed opportunity (%)	-	-	7

CMPs, carbon mitigation policies; CTP, carbon tax policy; COP, carbon offset policy; CCS, carbon capture and storage; MARR, minimum attractive return rate; IRR, internal rate of return.

on the parametric behavior of the system in the recovery and back to sustainability stages described in chapter 4. The system revenue is also determined based on the sum of electricity generated per year (Figure 4) and its supply price.[69] Obviously, first-year costs will be higher than other years due to widespread depletion of resources, which will lead to increment of costs and reduced profits from electricity sales.

According to the data of Table 11, the calculated IRR for each CMP is presented in Table 12.

Due to Table 12, IRR of the project under CTP and COP scenarios are equal (9%) while CCS experiences lower IRR (2%). It means, although the project under all CMPs is feasible, the CCS scenario leads to missing 7% annual profit rather than CTP and COP. In other words, considering the equal investment payback period, the attraction of investment on the project under CTP and COP is 7% higher than the CCS scenario. Regarding the IRR approach, CTP- and COP-based scenarios are equally the same, due to equal investment cost and equal IRR after 40 years. However, both CTP and COP models create the same long-term attraction of investment for stakeholders.

7 | CONCLUSION

This study is an optimization platform to minimize costs and DSR of implementing a bioenergy supply chain considering pre- and postdisaster conditions, disruptive scenarios, and various CMPs. To consider uncertainty of material availability, material quality, and consumer demand, a two-stage stochastic programming model has been provided in which the strategic and tactical decisions are made in the first and second stages, respectively.

We have considered the performance of a natural disaster (Katrina hurricane), as the start point of disruptions, in a real-world case study in the Mississippi State. Our research has categorized the decision-making space after the disaster into three substages including damage, recovery, and back to sustainability. To evaluate environmental considerations in the design and planning of the bioelectricity supply chain, two groups of CMPs including CTP and COP, as the PC-based

regulations, and CCS, as the TI-based approach, have been added to the model. The computational results showed the model under disruptive conditions and the CTP scenario experiences the highest DSR value (8,978,502 $).

Additionally, a financial analysis has performed to show economic feasibility and missed opportunities of different CMPs in the postdisaster condition. The results of the financial analysis showed that although the impact of uncertainty on the system under the influence of the CTP scenario results in the highest unexpected cost (DSR) equals to 8,978,502 $; however, the COP and CTP are the most cost-effective scenarios, respectively. They created the 9% as the IRR in the equal comparative terms (payback periods and MARR) while applying a CSS policy with 2% IRR created a 7% missed opportunity costs in comparison with them.

As future research opportunities in this field, we suggest considering a wider range of CMPs and analyzing their impacts on biomass supply chain performance. The ability to sell the captured or unused carbon in the market to improve the economic attractions of the bioenergy projects can be another interesting topic for investigation. It should be noted the future cash flows in this study have been considered as static values. As a result, considering the fluctuation of cost and profit elements with attention to the changes in electricity price and MARR in the future could be helpful to more accurate financial analysis.

NOMENCLATURE

Sets

l	Set of forestlands, $l \in \{1,2, \dots L\}$
i	Set of potential locations to construct storages, $i \in \{1,2, \dots, I\}$
k	Set of potential locations to construct power plants, $k \in \{1,2, \dots, K\}$
b	Set of power plant sizes, $b \in \{1,2, \dots, B\}$
r	Set of storage sizes, $r \in \{1,2, \dots, R\}$
m	Set of main material types, $m \in \{1,2, \dots, M\}$
n	Set of main material forms, $n \in \{1,2, \dots, N\}$
a	Set of postdisaster stages, $a \in \{1,2, \dots, A\}$
s	Set of disruptive scenarios $s \in \{1,2, \dots, S\}$
v	Set of electricity consumption sectors, $v \in \{1,2, \dots, V\}$
q	Set of potential locations to establish carbon capture unit, $q = \{1,2, \dots, Q\}$
y	Set of sizes to establish carbon capture unit, $y = \{1,2, \dots, Y\}$
h	Set of potential locations to establish geological storage, $h = \{1,2, \dots, H\}$
u	Set of sizes to establish geological storage, $u = \{1,2, \dots, U\}$
j	Set of pipeline sizes, $j = \{1,2, \dots, J\}$

Subsets

t_a — Set of time periods in post-disaster stage a

For each a, $t_a \in \{1, 2 \dots T_a\}$, $\sum_a t_a = \{1, 2 \dots T\}$

Parameters

$chrv_{mnl}$ — The cost per unit of harvesting material type m in form n in the forestland l

$cstr_{mni}$ — The cost per unit of holding material type m in form n in the storage i

$ftli_{mnli}$ — The fixed cost of transportation material type m in form n between forestland l to storage i

$vtli_{mnli}$ — The variable cost of transportation one unit of material type m in form n per each unit of distance between forestland l to storage i

$ftik_{mnik}$ — The fixed cost of transportation material type m in form n between storage i and power plant k.

$vtik_{mnik}$ — The variable cost of transportation one unit of material type m in form n per each unit of distance between storage i and power plant k

ic_{kb} — The investment cost of construction a power plant with size b in location k

fc_{kb} — The annually fixed operation and maintenance (O&M) cost of a power plant with size b in location k

vc_{kb} — The variable (O&M) cost of electricity generation per unit in the power plant with size b in location k

eff_{kb} — The efficiency of power plant with size b in location k

θ_{mn} — The weight loss rate of raw material type m, in form n

β_{t_a} — The level of safety stock in period t_a of stage a

cap_{ir}^{str} — The capacity of storage i with size r

cap_{kb}^{p} — The electrical capacity of power plant k with size b

cl_{vt_a} — The electricity consumption level of consumer v in period t_a of stage a

pr^s — The probability of occurrence disruptive scenario s

$j_{smnlt_a}^s$ — The maximum quantity of available resource type m, in form n in the forestland l in period t_a of stage a under scenario s

ev_{mnt_a} — The energy value of material type m in form n, in period t_a of stage

$aHhv_{mnt_a}$ — The higher heating value of material type m, in form n, in period t_a and stage a

Mc_{mnt_a} — The moisture content of material type m, in form n and period t_a and stage a

d_{li} — The distance between forestland l and storage i

d_{ik} — The distance between storage i and power plant k

d_{qh} — The distance between capture unit q and geological storage h

fsc_{yq} — The annually fixed O&M cost of the capture facility with size y in the location q

cc_{yq} — The carbon capture cost per unit, for a capture facility with size y in the location q

isc_{yq} — The investment cost to construct carbon capture facility with size y in the location q

igs_{uh} — The investment cost to construct a geological storage with size u in the location h

fgs_{uh} — The annually fixed O&M cost of the geological storage with size u in the location h

hg_{t_auh} — The cost of holding carbon in geological storage with size u in location h, at time t_a and stage a

tcs_{t_auh} — The target of capturing carbon in the geological storage with size u in location h, at time t_a and stage a

vtp_{jqh} — The variable cost of transportation one unit of carbon by pipeline with size j between capture unit q and geological storage h

ipj_{jqh} — The investment cost of construction the pipeline with size j between locations q and h

ftp_{jqh} — The fixed cost of carbon transportation by pipeline with size j between capture unit q and geological storage h

fpj_{jqh} — The annually fixed O&M costs of construct pipeline with size j between locations q and h

cap_{yq}^{cap} — The capacity of capture unit with size y in location q

cap_{uh}^{gs} — The capacity of geological storage with size u in location h

cap_{j}^{pip} — The capacity of the pipeline transportation with size j

eff_{yq} — The efficiency to absorption of CO_2 from the exhaust gas of power plant by capture unit with size y and in location q

eff_{jqh} — The efficiency of the pipeline with size j to transfer carbon from capture unit in location q to geological storage in location h

eff_{uh} — The efficiency of the geological storage with size u in the location h

Cap_{t_a} — The permitted emission capacity of carbon at time t_a and stage a

$ehrv_{mnl}$ — The CO_2 emission for harvesting one unit of material in type m in form n at forestland l

$esrt_{mni}$ — The CO_2 emission for holding one unit of material type m in form n at storage i

$feli_{mnli}$ — The fixed CO_2 emission for transporting material type m in form n, between forestland l and storage i

$veli_{mnli}$ — The variable CO_2 emission for transporting one unit of material type m in form n per each unit of distance, between forestland l and storage i

P_1 — The permitted numbers of locations to open storages

P_2 — The permitted numbers of locations to establish power plants

x_{ir} — Binary variable that is 1 if storage has been opened in location i with size r and 0 otherwise

x_{bk} — Binary variable, which is 1 if power plant has been established in location k with size b and 0 otherwise

x_{jqh} — Binary variable, which is 1 if the pipeline transportation facility with size j has been constructed between locations q and h and 0 otherwise.

Continues (Non-negative) Variables

$Qhrv^s_{mnt_al}$ — Quantity of harvested material type m in form n in the forestland l in period t_a of stage a under scenario s

$Qstr^s_{mnt_air}$ — Quantity of stored material type m in form n in the storage i with size r in period t_a of stage a under scenario s

$Qli^s_{mnt_alir}$ — Quantity of transported material type m in form n between forestland l and storage i with size r in period t_a of stage a under scenario s

$Qik^s_{mnt_airkb}$ — Quantity of transported material type m in form n between storage i with size r and power plant k with size b in period t_a of stage a under scenario s

$et^s_{t_abk}$ — Total volume of generated electricity in power plant k with size b in period t_a of stage a under scenario s

$ed^s_{t_abkv}$ — Volume of distributed electricity from power plant k with size b to consumption sector v in period t_a of stage a under scenario s

$feik_{mnik}$ — The fixed CO_2 emission for transporting one unit of material type m in form n, between storage i and power plant k

$veik_{mnik}$ — The variable CO_2 emission for transporting one unit of material type m in form n, each unit of distance between storage I and power plant k

$ecnv_{kb}$ — The CO_2 emission for conversion one unit of material at power plant k with size b

$etax$ — The CO_2 emission tax for a unit liberated carbon

cp — The price of purchasing one unit of surplus carbon

ω — The ideal target (cost of supply chain) that investors are willing to the realization of it

R — The maximum acceptable rate of downside risk for investors

B_1 — The permitted numbers of locations to establish capture unit

B_2 — The permitted numbers of locations to establish geological storage

Binary Variables

x_{yq} — Binary variable, which is 1 if the capture unit has been established in location q with size y and 0 otherwise

x_{uh} — Binary variable, which is 1 if the geological storage has been established in location h with size u and 0 otherwise

$spc^s_{t_a}$ — Amounts of surplus purchased CO_2 capacity

$DSR^s_{t_a}$ — Down side risk of scenario s in period t_a of stage a

$Ctp^s_{jt_ayquh}$ — Volumes of transferred carbon by pipeline with size j between capture unit q with size y and geological storage h with size u at time t_a and stage a under scenario s

$Csg^s_{t_auh}$ — Volumes of stored carbon in geological storage with size u in location h, at time t_a and stage a under scenario s

$Csc^s_{yqt_a}$ — Volumes of transferred CO_2 from power plants to capture unit with size y in location q, at time t_a and stage a under scenario s

ORCID

Mohammad Hossein Ahmadi https://orcid.org/0000-0002-0097-2534

REFERENCES

1. Owusu PA, Asumadu-Sarkodie S. A review of renewable energy sources, sustainability issues and climate change mitigation. *Cogent Eng*. 2016;3:1167990.
2. Ahmadi MH, Madvar MD, Sadeghzadeh M, Rezaei MH, Herrera M, Shamshirband S. Current status investigation and predicting carbon dioxide emission in latin American countries by connectionist models. *Energies*. 2019;12:1916.
3. Liu G, Li M, Zhou B, Chen Y, Liao S. General indicator for techno-economic assessment of renewable energy resources. *Energy Convers Manag*. 2018;156:416-426.
4. Dehghani Madvar M, Aslani A, Ahmadi MH, Karbalaie Ghomi NS. Current status and future forecasting of biofuels technology development. *Int J Energy Res*. 2019;43:1142-1160.
5. Carneiro MLNM, Gomes MSP. Energy, exergy, environmental and economic analysis of hybrid waste-to-energy plants. *Energy Convers Manag*. 2019;179:397-417.
6. Soliño M, Oviedo JL, Caparrós A. Are forest landowners ready for woody energy crops? Preferences for afforestation programs in Southern Spain. *Energy Econ*. 2018;73:239-247.
7. Zahraee SM, Golroudbary SR, Shiwakoti N, Kraslawski A, Stasinopoulos P. An investigation of the environmental sustainability of palm biomass supply chains via dynamic simulation modeling: a case of Malaysia. *J Clean Prod*. 2019;237:117740.
8. Shabani N, Sowlati T. Evaluating the impact of uncertainty and variability on the value chain optimization of a forest biomass power plant using Monte Carlo Simulation. *Int J Green Energy*. 2016;13:631-641.
9. Flisberg P, Frisk M, Rönnqvist M. FuelOpt: a decision support system for forest fuel logistics. *J Oper Res Soc*. 2012;63:1600-1612.
10. Cambero C, Sowlati T. Assessment and optimization of forest biomass supply chains from economic, social and environmental perspectives–A review of literature. *Renew Sustain Energy Rev*. 2014;36:62-73.
11. Laganière J, Paré D, Thiffault E, Bernier PY. Range and uncertainties in estimating delays in greenhouse gas mitigation potential of forest bioenergy sourced from Canadian forests. *GCB Bioenergy*. 2017;9:358-369.
12. Chan YH, Yusup S, Quitain AT et al Effect of process parameters on hydrothermal liquefaction of oil palm biomass for bio-oil production and its life cycle assessment. *Energy Convers Manag*. 2015;104:180-188.

13. Gustavsson L, Karlsson Å. CO 2 mitigation: on methods and parameters for comparison of fossil-fuel and biofuel systems. *Mitig Adapt Strateg Glob Chang*. 2006;11:935-959.

14. Antle J, Capalbo S, Mooney S, Elliott E, Paustian K. Spatial heterogeneity, contract design, and the efficiency of carbon sequestration policies for agriculture. *J Environ Econ Manage*. 2003;46:231-250.

15. Liu L, Huang G, Baetz B, Zhang K. Environmentally-extended input-output simulation for analyzing production-based and consumption-based industrial greenhouse gas mitigation policies. *Appl Energy*. 2018;232:69-78.

16. Shi B, Xu W, Wu W, Kuo P-C. Techno-economic analysis of oxy-fuel IGCC power plants using integrated intermittent chemical looping air separation. *Energy Convers Manag*. 2019;195:290-301.

17. Sekar RC, Parsons JE, Herzog HJ, Jacoby HD. Future carbon regulations and current investments in alternative coal-fired power plant technologies. *Energy Pol*. 2007;35:1064-1074.

18. Yi Q, Zhao Y, Huang YI et al Life cycle energy-economic-CO_2 emissions evaluation of biomass/coal, with and without CO_2 capture and storage, in a pulverized fuel combustion power plant in the United Kingdom. *Appl Energy*. 2018;225:258-272.

19. Pearce D. The role of carbon taxes in adjusting to global warming. *Econ J*. 1991;101:938-948.

20. Martin R, De Preux LB, Wagner UJ. The impact of a carbon tax on manufacturing: Evidence from microdata. *J Public Econ*. 2014;117:1-14.

21. Leeson D, Mac Dowell N, Shah N, Petit C, Fennell PS. A Techno-economic analysis and systematic review of carbon capture and storage (CCS) applied to the iron and steel, cement, oil refining and pulp and paper industries, as well as other high purity sources. *Int J Greenh Gas Control*. 2017;61:71-84.

22. Selma L, Seigo O, Dohle S, Siegrist M. Public perception of carbon capture and storage (CCS): a review. *Renew Sustain Energy Rev*. 2014;38:848-863.

23. Tan Y, Nookuea W, Li H, Thorin E, Yan J. Property impacts on Carbon Capture and Storage (CCS) processes: a review. *Energy Convers Manag*. 2016;118:204-222.

24. Nakaten N, Schlüter R, Azzam R, Kempka T. Development of a techno-economic model for dynamic calculation of cost of electricity, energy demand and CO_2 emissions of an integrated UCG–CCS process. *Energy*. 2014;66:779-790.

25. Porter RTJ, Fairweather M, Kolster C, Mac Dowell N, Shah N, Woolley RM. Cost and performance of some carbon capture technology options for producing different quality CO_2 product streams. *Int J Greenh Gas Control*. 2017;57:185-195.

26. Aliyon K, Hajinezhad A, Mehrpooya M. Energy assessment of coal-fired steam power plant, carbon capture, and carbon liquefaction process chain as a whole. *Energy Convers Manag*. 2019;199:111994.

27. Ayoub N, Elmoshi E, Seki H, Naka Y. Evolutionary algorithms approach for integrated bioenergy supply chains optimization. *Energy Convers Manag*. 2009;50:2944-2955.

28. Wang S, Jena U, Das KC. Biomethane production potential of slaughterhouse waste in the United States. *Energy Convers Manag*. 2018;173:143-157.

29. Song J, Yang W, Higano Y, Wang X. Modeling the development and utilization of bioenergy and exploring the environmental economic benefits. *Energy Convers Manag*. 2015;103:836-846.

30. De Laporte AV, Weersink AJ, McKenney DW. Effects of supply chain structure and biomass prices on bioenergy feedstock supply. *Appl Energy*. 2016;183:1053-1064.

31. Gumte KM, Mitra K. Bio-supply chain network design to tackle ethanol deficiency in India: a mathematical framework. *J Clean Prod*. 2019;234:208–224.

32. Shabani N, Akhtari S, Sowlati T. Value chain optimization of forest biomass for bioenergy production: a review. *Renew Sustain Energy Rev*. 2013;23:299-311.

33. Souza SP, Seabra JEA. Integrated production of sugarcane ethanol and soybean biodiesel: environmental and economic implications of fossil diesel displacement. *Energy Convers Manag*. 2014;87:1170-1179.

34. De Meyer A, Cattrysse D, Rasinmäki J, Van Orshoven J. Methods to optimise the design and management of biomass-for-bioenergy supply chains: a review. *Renew Sustain Energy Rev*. 2014;31:657-670.

35. Mirkouei A, Haapala KR. Integration of machine learning and mathematical programming methods into the biomass feedstock supplier selection process. *Proc. 24th Int. Conf. Flex. Autom. Intell. Manuf.*, DEStech Publications, Inc. 2014; 443–450. https://doi.org/10.14809/faim.2014.0443

36. Melo MT, Nickel S, Saldanha-Da-Gama F. Facility location and supply chain management–A review. *Eur J Oper Res*. 2009;196:401-412.

37. Zhou X, Zhang H, Qiu R et al A two-stage stochastic programming model for the optimal planning of a coal-to-liquids supply chain under demand uncertainty. *J Clean Prod*. 2019;228:10-28.

38. Poudel SR, Marufuzzaman M, Bian L. A hybrid decomposition algorithm for designing a multi-modal transportation network under biomass supply uncertainty. *Transp Res Part E Logist Transp Rev*. 2016;94:1-25.

39. van de Kaa G, Kamp L, Rezaei J. Selection of biomass thermochemical conversion technology in the Netherlands: a best worst method approach. *J Clean Prod*. 2017;166:32-39.

40. Son LH, Louati A. Modeling municipal solid waste collection: a generalized vehicle routing model with multiple transfer stations, gather sites and inhomogeneous vehicles in time windows. *Waste Manag*. 2016;52:34-49.

41. Shabani N, Sowlati T. A hybrid multi-stage stochastic programming-robust optimization model for maximizing the supply chain of a forest-based biomass power plant considering uncertainties. *J Clean Prod*. 2016;112:3285-3293.

42. Carlsson D, D'Amours S, Martel A, Rönnqvist M. Supply chain planning models in the pulp and paper industry. *INFOR Inf Syst Oper Res*. 2009;47:167-183.

43. Ren J, An DA, Liang H et al Life cycle energy and CO_2 emission optimization for biofuel supply chain planning under uncertainties. *Energy*. 2016;103:151-166.

44. Fattahi M, Govindan K. A multi-stage stochastic program for the sustainable design of biofuel supply chain networks under biomass supply uncertainty and disruption risk: a real-life case study. *Transp Res Part E Logist Transp Rev*. 2018;118:534-567.

45. Babazadeh R. Robust optimization method to green biomass-to-bioenergy systems under deep uncertainty. *Ind Eng Chem Res*. 2018;57:7975-7986.

46. Hombach LE, Büsing C, Walther G. Robust and sustainable supply chains under market uncertainties and different risk attitudes–A case study of the German biodiesel market. *Eur J Oper Res*. 2018;269:302-312.

47. Ortiz-Gutiérrez RA, Giarola S, Bezzo F. Optimal design of ethanol supply chains considering carbon trading effects and multiple technologies for side-product exploitation. *Environ Technol*. 2013;34:2189-2199.

48. Palak G, Ekşioğlu SD, Geunes J. Analyzing the impacts of carbon regulatory mechanisms on supplier and mode selection decisions: an application to a biofuel supply chain. *Int J Prod Econ*. 2014;154:198-216.

49. Marufuzzaman M, Eksioglu SD, Huang YE. Two-stage stochastic programming supply chain model for biodiesel production via wastewater treatment. *Comput Oper Res*. 2014;49:1-17.

50. Memari A, Ahmad R, Rahim ARA, Jokar MRA. An optimization study of a palm oil-based regional bio-energy supply chain under carbon pricing and trading policies. *Clean Technol Environ Policy*. 2018;20:113-125.

51. Akgul O, Mac Dowell N, Papageorgiou LG, Shah N. A mixed integer nonlinear programming (MINLP) supply chain optimisation framework for carbon negative electricity generation using biomass to energy with CCS (BECCS) in the UK. *Int J Greenh Gas Control*. 2014;28:189-202.

52. Santibanez-Gonzalez EDR. A modelling approach that combines pricing policies with a carbon capture and storage supply chain network. *J Clean Prod*. 2017;167:1354-1369.

53. d'Amore F, Bezzo F. Economic optimisation of European supply chains for CO_2 capture, transport and sequestration. *Int J Greenh Gas Control*. 2017;65:99-116.

54. The economics of forestry. 2013–2014 forest inventory southeast region. Mississippi: 2014http://www.forestryimpacts.net/reports/mississippi/MIFI_SE_13_14.pdf

55. Galea S, Tracy M, Norris F, Coffey SF. Financial and social circumstances and the incidence and course of PTSD in Mississippi during the first two years after Hurricane Katrina. *J Trauma Stress*. 2008;21:357-368.

56. Stevenson JR, Emrich CT, Mitchell JT, Cutter SL. Using building permits to monitor disaster recovery: a spatio-temporal case study of coastal Mississippi following Hurricane Katrina. *Cartogr Geogr Inf Sci*. 2010;37:57-68.z

57. Glass PA, Oswalt SN. Initial estimates of hurricane Katrina impacts of Mississippi gulf coast forest resources. Mississippi Inst For Invent 1–4 2007.

58. Shabani N. Value chain optimization of a forest biomass power plant considering uncertainties. 2014.

59. Hailwood AJ, Horrobin S. Absorption of water by polymers: analysis in terms of a simple model. *Trans Faraday Soc*. 1946;42:B084-B092.

60. Hameury S. Moisture buffering capacity of heavy timber structures directly exposed to an indoor climate: a numerical study. *Build Environ*. 2005;40:1400-1412.

61. Saghaei M, Ghaderi H, Soleimani H. Design and optimization of biomass electricity supply chain with uncertainty in material quality, availability and market demand. *Energy*. 2020;197:117165.

62. Prestemon JP, Holmes TP. Economic impacts of hurricanes on forest owners. Pye, John M; Rauscher, H Michael; Sands, Yasmeen; Lee, Danny C; Beatty, Jerome S, Tech, eds. Adv Threat Assess

63. Holmes TP. Price and welfare effects of catastrophic forest damage from southern pine beetle epidemics. *For Sci*. 1991;37:500-516.

64. Prestemon JP, Holmes TP. Market dynamics and optimal timber salvage after a natural catastrophe. *For Sci*. 2004;50:495-511.

65. Pahkinen E, Lehtonen R. Otanta-asetelmat ja tilastollinen analyysi. Gaudeamus; 1989.

66. Rentizelas AA, Tolis AJ, Tatsiopoulos IP. Logistics issues of biomass: The storage problem and the multi-biomass supply chain. Renew Sustain Energy Rev.

67. Khatiwada D, Leduc S, Silveira S, McCallum I. Optimizing ethanol and bioelectricity production in sugarcane biorefineries in Brazil. *Renew Energy*. 2016;85:371-386.

68. Lindner S, Peterson S, Windhorst W. An economic and environmental assessment of carbon capture and storage (CCS) power plants: a case study for the City of Kiel. *J Environ Plan Manag*. 2010;53:1069-1088.

69. EIA US. Mississippi Electricity Profile 2018 2019. https://www.eia.gov/electricity/state/mississippi/

70. DBCF. Mississippi department of banking and consumer finance. Discount certificate number 2019. https://www.dbcf.ms.gov/a/current-discount-rate/

71. Brown ML, Bulpitt WS, Walsh JL Jr. *Biomass and alternate fuel systems: an engineering and economic guide*. Hobken, NJ: John Wiley & Sons; 2011.

72. Sokhansanj S, Mani S, Turhollow A et al Large-scale production, harvest and logistics of switchgrass (Panicum virgatum L.)–current technology and envisioning a mature technology. *Biofuels, Bioprod Biorefining*. 2009;3:124-141.

73. Zhang F, Johnson DM, Wang J, Yu C. Cost, energy use and GHG emissions for forest biomass harvesting operations. *Energy*. 2016;114:1053-1062.

74. Mansuy N, Thiffault E, Lemieux S, Manka F, Paré D, Lebel L. Sustainable biomass supply chains from salvage logging of fire-killed stands: a case study for wood pellet production in eastern Canada. *Appl Energy*. 2015;154:62-73.

75. Heller MC, Keoleian GA, Mann MK, Volk TA. Life cycle energy and environmental benefits of generating electricity from willow biomass. *Renew Energy*. 2004;29:1023-1042.

APPENDIX A

Volumes of different types of greenwood materials in the southeast area of Mississippi[54]

County/ Material volumes (Green Ton)	Pine pulpwood	Pine saw timber	Hardwood pulpwood	Hardwood saw timber
1-Jefferson Davis	249 261	165 689	121 626	78 115
2-Covington	299 153	174 413	61 578	78 114
3-Jones	401 984	320 496	61 286	39 317
4-Wayne	648 329	496 631	177 192	121 723
5-Marion	390 912	286 865	73 368	37 214
6-Lamar	324 016	182 728	20 134	12 436
7-Forrest	361 753	218 279	24 608	15 108
8-Perry	517 760	317 461	35 093	20 646
9-Greene	682 324	482 739	63 546	36 360
10-Pearl River	414 072	306 753	32 565	25 588
11-Stone	283 904	214 243	34 769	26 885
12-George	369 115	271 849	90 452	76 430
13-Hancock	173 613	138 577	21 201	19 635
14-Harrison	227 356	176 869	14 580	9805
15-Jackson	338 150	185 978	88 251	33 692

APPENDIX B

Parameter values, units, and references.

Parameter	Value	Unit	Reference
Fixed transportation cost	5.16	$/GT	[72]
Variable transportation cost	0.1235	$/GT/Km	[72]
Fixed transportation emission	0.0764	Kg CO_2/GT	[49]
Variable transportation emission	0.05298	Kg CO_2/GT/Km	[49]
Green wood Harvesting cost	9.3	$/GT	[73]
Salvaged wood harvesting cost	10.2	$/GT	[73,74]
Harvesting emission	12	Kg/GT	[73]
Conversion emission	109	Kg/MWh	[75]
Capture unit investment cost	1878.5	$/KW	[25]
Pipeline investment cost	0.49	Million $/Km	[68]
Geological storage investment cost	14	Million $	[68]
CCS capture capacity	627.74	Kg CO_2	[25]
Geological storage capacity	1	Million Ton CO_2	[68]
Total CCS variable cost (including carbon capture and transportation costs by pipeline)	57.61	$/Kg CO_2	[25]
Emission tax	0.015	$/Kg CO_2	[49]
Carbon purchase cost	0.012	$/Kg CO_2	[49]
Carbon capacity	1 000 000	Kg CO_2	[49]

APPENDIX C

Monthly weather and material quality information.

County/Monthly Temperature (°C)	Jan H	Jan L	Feb H	Feb L	Mar H	Mar L	Apr H	Apr L	May H	May L	Jun H	Jun L	Jul H	Jul L	Ag H	Ag L	Sep H	Sep L	Oct H	Oct L	Nov H	Nov L	Dec H	Dec L
T_{dt} (°C)	+20.6	−12.9	+19.6	−8.6	+20	−7.6	+22	−2.06	+24.2	−2.06	+25.2		+26.2	+18.5	+26.4	+16.4	+26	+10.4	+26.0	−1.5	+21.4	−2.7	+21.8	−6.7
T_t °C	+15.4	+4.6	+17.8	+6.4	+21.4	+8.5	+25.6	+12.7	+29.1	+16.6	+32.6	+20	+32.3	+20.1	+33	+21.2	+30.9	+18.9	+26.5	+12.2	+21.3	+7.8	+16.9	+4.5
RH_t (%) (Humidity)	126	12.5	109	25	93	19.5	82	26.2					92	69.5	76	67	75.5	57.5	97.5	31.5	100	47.5	124	44
Mc_{mnt} (%)	8.1	1	7.17	2.32	6	1.32	5.5	1.57	5.55		4.3	3.8	5.62	4.37	5.07	4.75	5.1	3.6	6.5	1.75	6.67	2.63	8.5	2.37
Hhv_{mnt} (MWh)	5.59	5.19	5.52	5.24	5.57	5.31	5.56	5.34	5.55	5.36	5.43	5.40	5.40	5.33	5.38	5.36	5.37	3.91	5.55	5.28	5.50	5.27	5.52	5.17
ev_{mnt} (MWh/m^3)	5.12	4.40	4.99	4.5	5.08	4.62	5.06	4.66	5.05	4.71	4.83	4.77	4.77	4.65	4.74	4.70	4.71	3.48	5.04	4.56	4.95	4.54	4.98	4.37

APPENDIX D

Distance matrix between counties.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	7.75	20.63	48.55	79.1	25.76	47.62	48.3	69.91	101.1	67.61	83.24	104.88	127.83	117.4	142.6
2	20.44	12.21	30.49	58.13	35.14	40.55	29.36	50.97	82.16	64.59	64.29	85.94	108.89	98.46	123.66
3	48.55	30.49	10.3	29.61	60.39	45.17	30.49	41.53	58.65	69.21	68.92	69.09	113.51	103.08	109.6
4	79.1	58.13	29.61	7.58	89.79	74.33	60.74	46.91	43.71	98.47	76.08	60.7	142.15	133.61	102.05
5	25.76	35.14	60.39	89.79	10.83	33.05	34.66	53.65	84.84	62.84	55.94	88.62	85.69	90.11	115.31
6	47.62	40.55	45.17	74.33	33.05	12.8	15.31	28.05	59.24	26.8	29.91	63.02	71.09	64.08	89.28
7	48.3	29.36	30.49	60.74	34.66	15.31	12.1	18.28	50.47	38.12	35.5	54.25	83.24	69.67	94.87
8	69.91	50.97	41.53	46.91	53.65	28.05	18.28	12.1	31.36	50.11	32.36	35.23	94.41	66.93	75.77
9	101.1	82.16	58.65	43.71	84.84	59.24	50.47	31.36	9	81.03	53.71	20.9	110.49	93.95	60.91
10	67.61	64.59	69.21	98.47	62.84	26.8	38.12	50.11	81.03	13.2	24.85	59.18	46.3	48.63	82.78
11	83.24	64.29	68.92	76.08	55.94	29.91	35.5	32.36	53.71	24.85	10.31	35.26	51.33	34.68	59.88
12	104.88	85.94	69.09	60.7	88.62	63.02	54.25	35.23	20.9	59.18	35.26	10.66	92.05	75.51	42.47
13	127.83	108.89	113.51	142.15	85.69	71.09	83.24	94.41	110.49	46.3	51.33	92.05	9.58	16.23	57.93
14	117.4	98.46	103.08	133.61	90.11	64.08	69.67	66.93	93.95	48.63	34.68	75.51	16.23	10.91	41.02
15	142.6	123.66	109.6	102.05	115.31	89.28	94.87	75.77	60.91	82.78	59.88	42.47	57.93	41.02	9.71

Author/s:
Saghaei, M;Dehghanimadvar, M;Soleimani, H;Ahmadi, MH

Title:
Optimization and analysis of a bioelectricity generation supply chain under routine and disruptive uncertainty and carbon mitigation policies

Date:
2020-08-01

Citation:
Saghaei, M., Dehghanimadvar, M., Soleimani, H. & Ahmadi, M. H. (2020). Optimization and analysis of a bioelectricity generation supply chain under routine and disruptive uncertainty and carbon mitigation policies. Energy Science and Engineering, 8 (8), pp.2976-2999. https://doi.org/10.1002/ese3.716.

Persistent Link:
http://hdl.handle.net/11343/274077