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A mixed biomass-based energy supply chain for enhancing economic and environmental sustainability benefits: A multi-criteria decision making framework

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HIGHLIGHTS

- A mixed supply chain is developed to enhance sustainability benefits of bioenergy.
- A decision-making framework is constructed to balance sustainability dimensions.
- A stochastic optimization model is developed to explore the effects of uncertainty.
- This study provides insights on bio-oil production processes and system structure.

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Biomass
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Bio-oil
Mobile bio-refinery
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ABSTRACT

Bioenergy sources have been introduced as a means to address challenges of conventional energy sources. The uncertainties of supply-side (upstream) externalities (e.g., collection and logistics) represent the key challenges in bioenergy supply chains and lead to reduce cross-cutting sustainability benefits. We propose a mixed biomass-based energy supply chain (consisting of mixed-mode bio-refineries and mixed-pathway transportation) and a multi-criteria decision making framework to address the upstream challenges. Our developed framework supports decisions influencing the economic and environmental dimensions of sustainability. Economic analysis employs a support vector machine technique, to predict the pattern of uncertainty parameters, and a stochastic optimization model, to incorporate uncertainties into the model. The stochastic model minimizes the total annual cost of the proposed mixed supply chain network by using a genetic algorithm. Environmental impact analysis employs life cycle assessment to evaluate the global warming potential of the cost-effective supply chain network. Our presented approach is capable of enhancing sustainability benefits of bioenergy industry infrastructure. A case study for the Pacific Northwest is used to demonstrate the application of the methodology and to verify the models. The results indicate that mixed supply chains can improve sustainability performance over traditional supply infrastructures by reducing costs (up to 24%) and environmental impacts (up to 5%).

1. Introduction

1.1. Motivation

Bioenergy has been suggested as a sustainable source of energy that has high potential to displace fossil-based energy [1]. Sustainable bioenergy sources can promote economic opportunities, energy security, and environmental benefits [2]. Biomass, as a key bioenergy resource, can be produced from natural materials, such as forest harvest residues (FHR), energy crops, algae, and agricultural wastes [3,4]. Biomass represents a promising renewable resource due to its domestic abundance and low price. Biomass-based energy from a combination of sources (forest, agricultural, and algal) comprises the largest portion (50%) of renewable energy resources in the U.S. [5]. The enormous domestic biomass potential (one-billion-ton annual supply) can meet commercialization and sustainability goals, which is critical to long-term viability for renewable energy. The replacement of fossil energy imports with bioenergy can address environmental pressures and offer

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Nomenclature

Indices

c	collection
dt	double-trailer truck
f	fixed bio-refinery
i	set of collection sites
j	set of staging sites
k	set of mobile (portable) bio-refinery sites
l	set of fixed (nonportable) bio-refinery sites
m	mobile bio-refinery
M	large positive constant
p	pre-processing
s	staging
st	single-trailer truck
t	set of time periods
tt	tanker truck

Parameters

A	biomass accessibility rate
Cap_i	annual capacity of a collection site (metric tons)
Cap_m	annual capacity of a mobile bio-refinery (metric tons)
Cap_f	annual capacity of a fixed bio-refinery (metric tons)
D	distance of collection site to a portable bio-refinery or fixed bio-refinery location (miles)
EF_{mass}	total GHG emissions factor of biomass transportation (kg CO_2 eq. per ton-mile) – the ton is equal to 1000 Kg in this study
$EF_{mass}CO_2$	CO_2 emissions factor of biomass transportation (kg CO_2 per ton-mile)
$EF_{mass}CH_4$	CH_4 emissions factor of biomass transportation (kg CH_4 per ton-mile)
$EF_{mass}N_2O$	N_2O emissions factor of biomass transportation (kg N_2O per ton-mile)
EF_{oil}	total GHG emissions factor of bio-oil transportation (kg CO_2 eq. per ton-mile)
$EF_{oil}CO_2$	CO_2 emissions factor of bio-oil transportation (kg CO_2 per ton-mile)
$EF_{oil}CH_4$	CH_4 emissions factor of bio-oil transportation (kg CH_4 per ton-mile)
$EF_{oil}N_2O$	N_2O emissions factor of bio-oil transportation (kg N_2O per ton-mile)
EF_{pro}	total GHG emissions factor of production process (kg CO_2 eq. per ton)
$EF_{pro}CO_2$	CO_2 emissions factor of production process (kg CO_2 per ton)
$EF_{pro}CH_4$	CH_4 emissions factor of production process (kg CH_4 per ton)
$EF_{pro}N_2O$	N_2O emissions factor of production process (kg N_2O per ton)
EF_{up}	total GHG emissions factor of upstream activities (kg CO_2 eq. per ton)
$EF_{up}CO_2$	CO_2 emissions factor of upstream activities (kg CO_2 per ton)
$EF_{up}CH_4$	CH_4 emissions factor of upstream activities (kg CH_4 per ton)
$EF_{up}N_2O$	N_2O emissions factor of upstream activities (kg N_2O per ton)
F_{site}	annual fixed cost for a defined site, e.g., collection, staging, refinery, or storage ($)
F_{truck}	annual fixed cost of a defined truck, e.g., single-trailer, double-trailer, or tanker trucks ($)
G_{mass}	GWP of biomass transportation (kg CO_2 eq.)
G_{oil}	GWP of bio-oil transportation (kg CO_2 eq.)
G_{pro}	GWP of production process (kg CO_2 eq.)
G_{up}	GWP of upstream activities (kg CO_2 eq.)
L_{site}	annual labor cost for a defined site, e.g., collection, staging, refinery, or storage ($)
L_{truck}	annual labor cost of a defined truck, e.g., single-trailer, double-trailer, or tanker trucks ($)
M_{mass}	mass of available biomass (metric tons)
M_{pro}	mass of processed biomass (metric tons)
N	base number of collection sites
PY	percentage yield of converting biomass to bio-oil
O_{pro}	mass of bio-oil produced (metric tons)
q_{ij}	biomass quality rate
RCO_2	CO_2 emissions rate (kg CO_2 eq./kg CO_2)
RCH_4	CH_4 emissions rate (kg CO_2 eq./kg CH_4)
RN_2O	N_2O emissions rate (kg CO_2 eq./kg N_2O)
U_c	annual utilization of a forwarder (metric tons per year)
U_{dt}	annual utilization of a double-trailer truck (metric tons per year)
U_f	annual processing of a fixed bio-refinery (metric tons per year)
U_m	annual processing of a portable bio-refinery (metric tons per year)
U_p	annual utilization of a grinder (metric tons per year)
U_{st}	annual utilization of a single-trailer truck (metric tons per year)
U_{tt}	annual utilization of a tanker truck (metric tons per year)
V_{site}	annual variable cost for a defined site, e.g., collection, staging, refinery, or storage ($ per year)
V_{truck}	annual variable cost of a defined truck, e.g., single-trailer, double-trailer, or tanker trucks ($ per year)
α	quality rate of processed biomass
β	accessibility rate of processed biomass
θ	annual available mass of biomass (metric tons per year)

Continuous variables

X_{ijt}	mass of biomass (metric tons) transported from site i to site j during time period t
X_{ikt}	mass of biomass (metric tons) transported from site i to site k during time period t
X_{jlt}	mass of biomass (metric tons) transported from site j to site l during time period t

Integer variables

Y_{kst}	mass of bio-oil (metric tons) transported from site k to site s during time period t
Y_{lst}	mass of bio-oil (metric tons) transported from site l to site s during time period t

Binary variables

B_{ijt}	binary variable for transportation from site i to site j during time period t

significant opportunities for domestic job creation. For instance, it is estimated that the transportation sector accounts for two-thirds of U.S. oil consumption and generates one-third of U.S. greenhouse gas (GHG) emissions [3], which can be reduced through the increased production and use of bio-oil.

The need for scaling up bioenergy production derives from national priorities to [6]: reduce dependence on foreign oil, enhance energy security through the use of diverse domestic and clean energy resources, establish advanced bio-industries and rural economies, and mitigate environmental impacts from fossil fuel production and consumption, such as climate change. Some potential dramatic consequences of climate change include increasing forest fire severity, droughts affecting agricultural lands, the rise of ocean levels, and severe storms, as evidenced over the last decade; which is why government agencies (e.g., U.S. Department of Energy (DOE)), are committed to addressing these effects through clean energy solutions [7].

1.2. Challenges

Societal interest in bioenergy has increased scrutiny on system analysis and integration, cross-cutting sustainability, and integrated bio-refineries to address commercialization and sustainability challenges. However, according to the U.S. DOE, only 45% of combined resources from forest residues to crop residues is consumed due to logistical challenges, such as low energy density, high collection and transportation costs, land use competition, and immature, underdeveloped production technologies [8]. Biomass can address energy security challenges, including supplementing fossil-driven energy. Accordingly, special attention should be placed on developing biomass-based energy sources and technologies. Although biomass is a bioenergy resource that can potentially be harvested and replenished indefinitely, its sustainability performance should be evaluated by considering the economic, environmental, and social aspects across the biomass-based energy supply chain (BESC) [9].

The transition from conventional energy to biomass-based energy solutions presents numerous challenges. Ongoing research and innovations are pursuing methodological and technological breakthroughs for bio-refinery capital cost reduction and process scale-up for commercialization [10,11]. Most FHR are underutilized and often burned on site due to logistical challenges and low market value [1]. Challenges have also been reported throughout the literature due to the nature of BESCs [12]. A major BESC management challenge is considering uncertainty in supply, logistics, production yield, distribution, and demand. In order to overcome these challenges, development of robust BESCs that incorporate knowledge of the sources of uncertainty is crucial [12,13]. In particular, developing an optimization methodology for sustainable BESCs is an expedient short-term solution to trade off between cost and environmental impacts, as explored herein.

1.3. Background

Optimal supply chain (SC) planning aids decision makers to ensure the efficiency and effectiveness of material and information flows [14,15]. In the competitive energy market, the focus should be on minimizing negative social, economic, and environmental impacts to optimize SCs from a sustainability perspective. However, each segment of a BESC strives to maximize its own inherent objectives. BESCs encompass several entities within three main segments: upstream, midstream, and downstream (Fig. 1). A detailed overview of upstream and midstream BESC segments has been provided by Mirkouei et al. [1]. Further, BESC decisions are influenced by dynamic, real-world socio-economics; therefore, unsustainable and suboptimal system-level solutions must be mitigated through robust business and policy decision making as BESCs emerge. In addition to clean energy supply, optimal BESCs can benefit society through enhanced forest economies and workforce development from feedstock supply to bioenergy distribution.

Techno-economic optimization models have been widely used over the past half century to address cross-cutting sustainability challenges. Such optimization models can be applied to select cost-effective transportation pathways, bio-refinery locations, and conversion technologies. Techno-economic modeling was first applied to study biomass-based energy in the 1980s [16]. Additionally, one of the first techno-economic studies for bioenergy production, conducted by Solantausta et al. [17], compared pyrolysis and liquefaction conversion technologies for bioenergy (gasoline and fuel oil substitute) production from biomass feedstocks (wood, peat, and straw). They predicted the lowest cost for transportation fuel process would be \$12/GJ. Later, Mitchell et al. [18] developed a decision support system to facilitate techno-economic analysis of bioenergy SC infrastructure. They considered various feedstocks and conversion technologies. Their results indicate the direct effects of transportation cost and conversion cost on the prices of the entire SC. More recently, De Jong et al. [19] conducted techno-economic assessments of six conversion pathways to match the price of bio-jet fuel production with petroleum jet fuel price. Their analysis reported that none of the bioconversion pathways was able to match the price of petroleum jet fuel [20].

Prior studies of biomass-to-bio-oil SCs indicate that interest has increased in the bioenergy industry, especially due to the potential for near carbon neutrality in comparison with heating oil and fuel oil. Carbon neutrality occurs when carbon released into the environment during forest biomass combustion is nearly equal to the carbon absorbed from the atmosphere during the growth life of the tree (via photosynthesis) [21]. Therefore, quantitative assessment of bio-oil has been widely applied to meet commercialization targets, which the main approaches can be classified into the following four types:

1. Cost Calculation: This approach includes summing the partial costs of each entity in the SC. Badger et al. [22] applied this approach to report the cost of bio-oil production from biomass using a mobile pyrolysis refinery.
2. Geographic Information Systems (GIS): GIS-based approaches play a significant role in providing inputs for spatial analysis and optimization modeling. Zhang et al. [23] developed a decision support system using GIS-based analysis to identify potential bioethanol facility locations.
3. Simulation: This approach can ease decision making due to high modeling flexibility. Several combined methods proposed in the literature have applied simulation with GIS or optimization, such as Zamora-Cristales et al. [24] and Zhang et al. [25], to provide an integrated decision support system for BESC management.
4. Operations Research: A large number of BESC studies have applied operations research approaches, which can be divided into three main modeling groups: deterministic [26], stochastic [27], and

Fig. 1. Biomass-based Energy Supply Chain (BESC).

multi-objective [28].

Over the past three decades, numerous operations research studies have been conducted to support BESC developments [1]. Ba et al. [29] provided a detailed overview of operations research approaches (deterministic, stochastic, and multi-objective modeling) in the BESCs.

- **Deterministic Modeling.** Deterministic models can be classified by objective functions and decision variables into four groups: linear programming (LP), non-linear programming (NP), integer programming (IP), mixed integer linear programming (MILP), and mixed integer nonlinear programming (MINLP). Additionally, deterministic modeling has been widely used over the last half century to minimize the total cost of the entire BESCs (focusing on biomass supply and logistics) [29]. The results of prior studies indicate that biomass moisture content, chip size, and bio-refinery size have direct impacts on sustainable bioenergy production, particularly economic and environmental aspects of bio-oil SCs [1,30].
- **Stochastic Modeling.** Stochastic modeling provides analytical methods for decision makers to incorporate uncertainties into SC performance evaluation. Details about modeling uncertainties in SCs and stochastic programming optimization in BESCs have been previously reported by Shabani and Sowlati [31] and Awudu and Zhang [12]. Stochastic optimization manages uncertainty sources by considering probability distributions of input parameters based on the historical data, while deterministic models require known parameter values [12]. Analytical methods incorporate uncertainties into deterministic models to develop stochastic models, such as stochastic LP, stochastic MILP, and Markov chain modeling approaches. The most common simulation methods used to model BESC uncertainties are Monte Carlo [32] and discrete event [12] simulation. The major challenge of stochastic programming is designing a reliable computational algorithm to effectively solve the model [33], which is why fewer studies have considered parameter uncertainties [12]. The existing analytical and simulation methods used to incorporate the uncertainties in SCs depend on the types of uncertainties, such as operational (day-to-day implications) [32,34], tactical (short-term implications) [35,36], and strategic (long-term implications) [37].
- **Multi-objective Modeling.** Multi-objective models can trade-off between conflicting objectives (e.g., social, economic, and environmental) in sustainable and optimal planning of BESCs and provide a set of trade-off optimal solutions instead of a single optimal solution [38]. Multi-objective approaches have been widely used in systems engineering [39]. An overview of multi-objective modeling to support decisions in BESCs was reported by Cambero and Sowlati [39]. The main benefit of this approach is that the reliability of results is improved by considering several important factors in the decision. However, trading off between the objectives and selecting an optimal solution is not an easy task.

Uncertainties in biomass supply exist due to the natural characteristics of this energy resource. Biomass characteristics in upstream forest SCs include variations in quality (moisture content and energy density) and accessibility in upstream forest biomass SCs. These factors, especially biomass quality, affect the profitability of bioenergy production in different seasons. Seasonality has a major impact on ensuring a continuous supply at the desired moisture content; this means some biomass types may not be obtainable throughout the year. Since the present uncertainties add complexities to decision making in energy industries, a method for managing uncertainty sources is vital during BESC development [31]. Without considering uncertainty parameters, the results of SC models may be suboptimal, or even infeasible, and, subsequently, the results will be unreliable [31]. Key sources of uncertainty in upstream and midstream BESC segments are related to biomass supply (collection), logistics (transportation), pretreatment (size reduction and drying), and manufacturing processes (pre- and post-conversion) [12]. Thus, decision makers need to consider multiple sources of biomass to ensure supply chain robustness. Logistics uncertainties include facility location, transportation lead time, and transportation cost. Pretreatment uncertainties include equipment costs and unexpected equipment unavailability. Process uncertainties include production yield and unplanned machine unavailability.

There are at least two deficiencies in prior studies: (1) considering upstream uncertainties in BESC modeling and (2) a multi-criteria decision making framework and reliable computational methods do not exist to facilitate the identification of sustainable BESC networks. This study attempts to bridge the existing research gaps by (a) applying a mixed BESC system structure, (b) evaluating the competitive potential of mixed-mode process-level operations, and (c) incorporating the uncertainties of externalities involved. To this end, this study explores the effects of uncertainty in biomass supply by using stochastic MILP and genetic algorithm (GA) techniques. Use of GA with simulation methods is a promising approach for solving supply chain problems under stochastic circumstances, such as uncertain quality, delivery time, demand, and quantity shipped, particularly for larger problems [40,41]. GA is an evolutionary search heuristic, which employs several evolutionary phases (e.g., initialization, tournament selection, crossover, and mutation) to find a high-quality solution.

The focus of this study is on upstream and midstream segments of BESCs, which involve biomass collection, transportation, pretreatment, conversion, and short-term storage of bio-oil. The conversion process converts biomass into denser energy carriers (e.g., bio-oil and biochar) that ease subsequent handling, transportation, and storage. This study also concentrates on a tactical decision making (medium-term decisions of 6–12 months) to support sourcing and logistical decisions in a timely and profitable manner. Biomass sourcing decisions play a vital role in BESC development through the efficient collection, transporting, preprocessing, and pretreating of biomass to meet sustainability goals [42]. As an application of this research, both optimal and sustainable approaches are examined for the development and conversion of biomass feedstock into bio-oil.

Since the utilization of bioenergy aims to accommodate sustainability pressures, new bioenergy technologies need to be assessed with regard to economic, social, and environmental impacts. Decision makers can take steps to avoid the impacts of fossil fuel-based GHG emissions by promoting the use of bioenergy sources. GHG emissions are often expressed as CO_2 equivalent (CO_2 eq.) emissions and include several substances, e.g., carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) [26]. Environmentally responsible bio-resource stewardship supports mitigation of GHG emissions, soil degradation, poor water quality, and biodiversity loss [43]. In fact, renewable energy sources can potentially be carbon neutral, which is especially seen with biomass from commercial harvest residues. *Utilization of biomass from forest harvest residues is particularly effective, as these residues are typically burned in the field following commercial harvest as part of site preparation for planting, fire risk reduction, and rodent control.* On the other hand, it has been reported that cutting and burning trees, specifically for energy, as opposed to utilizing forest harvest residues, emits approximately 30% more carbon emissions than coal, requiring over 20 years to reabsorb the additional emissions [44]. Our study below considers a 20-year time horizon in calculating the global warming potential (GWP) of bio-oil production from forest harvest residues.

Relevant to the work herein, life cycle assessment (LCA) offers a standardized approach to evaluate environmental impacts of the SC system and assist in defining more environmentally responsible networks. Prior LCA studies of BESCs indicate a strong dependency of impact assessment results on the selected system boundary, allocation method, time horizon, and functional unit [45]. For instance, a system that maximizes the GHG emissions reductions per unit of energy is not able to achieve the highest GHG reduction per unit of biomass [45]. As mentioned in earlier studies [21,33], researchers have extensively used

LCA methods to conduct environmental impact assessments due to the availability of existing databases for industrial and supply chain processes. This study applies LCA to quantify resource consumption (e.g., biomass and fossil fuel), as well as emissions, to determine environmental impacts in terms of GWP for a mixed BESC. The GWP of a mixed BESC is then compared to that of a traditional BESC. The proposed mixed SC network includes mixed-mode bio-refineries (i.e., mobile and fixed) and mixed-pathway transportation (i.e., new and traditional) (Fig. 2).

The mobile bio-refinery considered is a trailer-mounted unit that uses pyrolysis technology to convert underutilized forest biomass to bio-products, such as bio-oil and biochar [1]. The mobile bio-refinery operates using biochar and syngas, as heat energy, in place of fossil fuels (e.g., diesel and gasoline) or electricity [46]. The major benefit of a mobile bio-refinery is its ability to produce higher energy density intermediate products in close proximity to raw materials (e.g., forests or farms) [26]. This alleviates transferring low-energy density biomass to centralized bio-refineries, which can improve the economic and environmental performance of bio-oil production by reducing transportation, handling, and storage operations [26].

Pyrolysis conversion technology involves thermochemical decomposition of biomass at a higher temperature (300–650 °C) in the absence of oxygen (Fig. 3) [33]. Three types of pyrolysis have been introduced in the literature: slow, intermediate, and fast processes. Each type has a specific reaction time and temperature, and production yield [47]. The main products include pyrolysis oil (bio-oil), pyrolysis char (biochar), and non-condensable gases (syngas), of which bio-oil and bio-char are target products. Bio-oil is a complex oxygenated compound mainly produced from biomass feedstock through a pyrolysis process that condenses vapors into a mixture of water and oxygenated carbon. Bio-oil includes carbon (55–64 wt%), hydrogen (5–8 wt%), oxygen (27–40 wt%), nitrogen (0.05–1 wt%), and ash (0.03–0.3 wt%) [48]. Bio-oil has an approximate density of 1.2 kg/L and a higher heating value of 18 MJ/kg [21]. Major applications of bio-oil include upgrading to transportation fuel, use in chemical production, and combustion in boilers, engines, and turbines [49]. Bio-oil has also been used to produce electricity, but it requires technical advancements to be commercialized [1].

1.4. Objective

The primary objective of this study is to explore the economic and environmental sustainability benefits of bio-oil production from forest biomass using a mixed supply chain, consisting of mixed-pathway transportation and mixed-mode bio-refineries. Therefore, a multi-criteria decision-making framework is developed to evaluate the mixed BESC from economic and environmental perspectives. The framework integrates economic analysis (mathematical cost modeling) and environmental impact analysis (life cycle assessment) to couple two of the primary dimensions of sustainability, consequently promoting clean energy solutions, rural communities, and forest economies. Evaluation of the social dimension of sustainability is outside of the scope of this work.

The paper is structured as follows: we present the multi-criteria decision making framework in Section 2 to evaluate the objectives of cost and environmental impacts, and to assess the role of network uncertainties and the mixed SC in supporting broader biomass-based energy commercialization. In Sections 3 and 4, we apply the developed framework to our undertaken case study as a demonstration and discuss the key parameters, results, and outcomes. Finally, we conclude by discussing economic feasibility and environmental implications of bio-oil production using mixed BESC.

2. Materials and methods

The multi-criteria decision-making framework presented herein for mixed BESCs improves upon traditional approaches by integrating centralized and distributed BESC configurations, incorporating biomass quality and accessibility uncertainties in supporting mathematical models, and implementing stochastic programming to accommodate changing business environments and natural conditions. The BESC decision making framework includes a set of qualitative (i.e., data classification, spatial analysis, and decision making) and quantitative (i.e., techno-economic analysis, stochastic optimization, scenario analysis, and life cycle assessment) methods. The framework assesses costs and environmental impacts associated with transforming biomass feedstocks into more sustainable and higher-quality bioenergy sources. Decision makers (e.g., policy makers and supply chain managers) will benefit from the integration of information about relevant resources, technologies, and processes within the framework that enhance sustainability across the bioenergy industry. To address the primary objective of this study (Section 1.4), the decision making framework developed herein encompasses the following three steps (Fig. 4):

Step 1. Exploration of various transportation configurations (mixed-mode pathways) to facilitate feedstock collection.
Step 2. Exploration of primary techno-economic parameters of integrated bio-refineries (mixed-mode refineries) to promote bioenergy production.
Step 3. Exploration of environmental and cost-competitive strategies to enhance sustainability benefits.

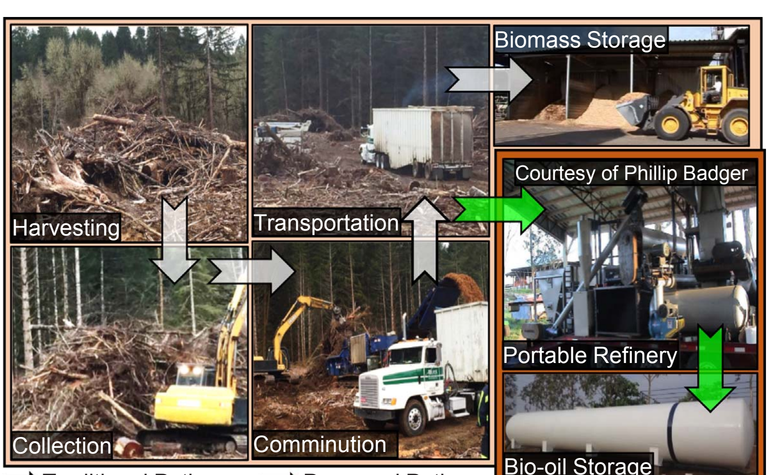

Fig. 2. Upstream BESC components: traditional pathway data collected near Lorane, OR; Mixed pathway has not been implemented.

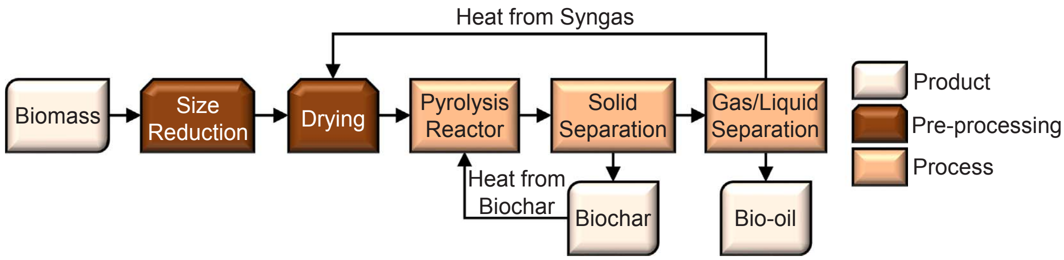

Fig. 3. Pyrolysis conversion process schematic.

These three steps are followed within this framework under two integrated phases: Economic analysis (Phase 1) and environmental analysis (Phase 2). Each phase is described in more detail in Sections 2.1 and 2.2, respectively.

2.1. Economic analysis (Phase 1)

The stochastic optimization model presented herein assists exploration of the commercial feasibility of bio-oil production by minimizing annual BESC costs, including collection, grinding, pyrolysis, and short-term storage costs. To assess the effects of uncertainties on the economic feasibility of bio-oil production, the model incorporates upstream BESC supply uncertainties by using two stochastic constraints as objectives. A metaheuristic computational algorithm is developed to solve the stochastic optimization model using GA as an artificial intelligence technique with the assistance of MATLAB®. The model utilizes uncertainty parameters estimated using support vector machine (SVM), a supervised machine learning method, which uses historical data to predict the future trends for parameters of interest. The solution found using SVM is always unique and is equivalent to solving a linear constrained, quadratic programming problem [50–53]. In this study, SVM provides a learning algorithm for pattern recognition of uncertainty parameters (i.e., biomass quality and accessibility rate outputs). Biomass quality and accessibility are highly influential and variable uncertainties in biomass supply - considering these parameters is essential for establishing sustainable bioenergy infrastructure [1].

For this study, biomass quality rate is a percentage indicator determined through SVM based on the non-combustibles (ash) content (% of dry weight) and moisture content (% of wet weight). Ash content is the solid fraction remaining after the complete combustion of biomass. Higher ash content of biomass generally indicates a reduced heating value. The range of ash contents for forest biomass ranges from 0.3 to 26.7% with an average of 6% [54]. Moisture content is the amount of water (H_2O) contained in the biomass. Forest harvest residues typically have a moisture content of at least 50–60% (wet basis) [1]. Due to lack of ash content and moisture content data for each site, values were randomly generated between the aforementioned ranges for each factor using uniform distributions. Next, biomass accessibility had to be determined. The biomass accessibility rate is a percentage indicator determined through SVM based on the available amount of biomass and distance of the biomass to the staging site. In this study, the available amount of biomass is obtained from the State of Oregon Department of Forestry (ODF). The shortest-path distance between the sites (from biomass collection to both types of refineries) is calculated using ArcGIS 10.1 software. A dataset is developed using data from each collection site data (biomass quality and accessibility) and forms a training dataset (Table 1) and testing dataset, which contain input and output information. In the developed dataset, biomass accessibility data are real data obtained from ODF (presented in Supplementary Materials section) and biomass quality data are randomly generated between the defined ranges by prior studies, ash content (0.3–26.7%) and moisture content (50–60%) [54,55]. The ash content, moisture content, available biomass, and distance to staging site define the input information. Also, the biomass quality rate and accessibility rate define the output information for each collection site, which would be obtained from the land manager and decision makers. Training and testing datasets are used in SVM to generate a learning algorithm for pattern recognition of uncertainty parameters. From the developed dataset, values for 10 collection sites are used as a training dataset and 10 collection sites as a testing dataset.

Table 1
Training dataset for collection sites.

Site No.	Average Ash Content (%)	Average Moisture Content (%)	Quality Rate (%)	Available Biomass (hundred tons)	Distance to Staging Site (miles)	Accessibility Rate (%)
1	3	5.5	7.5	11	12	6
2	2.5	6	7	14	10	7.5
3	3.5	5	7	12	16	5.5
4	2	6	8	19	5	9.5
5	2.3	5.5	8	14	9	8
6	3.5	6	6	12	12	6.5
7	3	6	6.5	13	9	7.8
8	3.4	5.5	6.5	11	10	6.5
9	2.1	6	7.5	15	15	6
10	2.5	5	8.5	10	11	6

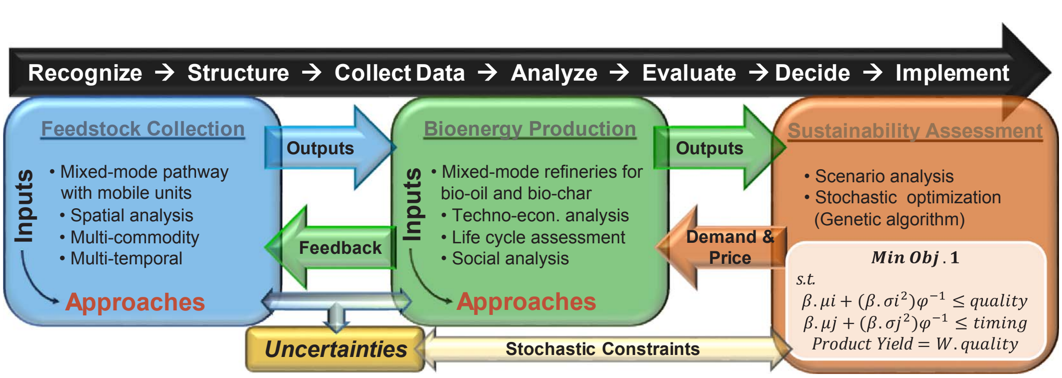

Fig. 4. BESC multi-criteria decision making framework (symbols are defined in the Nomenclature section).

SVM predicts the trend and generates the weight vectors for each factor (e.g., ash content and distance) by using SVM learning algorithms (classification and regression analysis) and the training inputs and outputs from the training phase [56]. The SVM weights (Table 2) are a linear combination of the training inputs and outputs that have been used to interpret the SVM models. These weights represent the coordinates of a vector perpendicular to the decision surface, or hyperplane. In this study, we used R programming language to generate the weights needed for the weight vector (R codes are provided in the Supplementary Materials).

The weights found in the training phase help decision makers determine the SVM outputs (i.e., quality and accessibility rates) of other collection sites. The weights from the training phase (Table 2) can be compared with the weights calculated in the testing phase (Table 3) to check the failure rate (difference between the training and testing weights). The failure rate was quite low (details are provided in Supplementary Materials). The biomass quality rate and accessibility rate (Q_t and A_t) for each collection site can be predicted after defining the weights for each factor. The quality and accessibility rates are used to classify the qualified and unqualified collection sites and, consequently, to select the high potential collection sites. Finally, Q_t and A_t are applied in the stochastic constraints (Constraints 2 and 3) within the optimization model.

After recognizing the pattern of uncertainty parameters (quality and accessibility), a stochastic optimization model is formulated to optimize total BESC cost over a one-year time horizon. The stochastic optimization model is applied in Phase 1 (economic analysis) as an analytical method to explore the commercial feasibility of bio-oil production. The objective function (Eq. (1)) includes collection, staging, transportation, pretreatment, conversion, and short-term storage costs to minimize the total annual cost (TC) of the BESC. The model encompasses two other objectives (quality rate and accessibility rate) that are defined as stochastic constraints (Eqs. (2) and (3) to incorporate the role of uncertainties. The model considers other constraints as follows: capacity (Eqs. (4)–(6)), collection base (number of collection sites) (Eq. (7)), production yield (Eq. (8)), conservation of flows (Eqs. (9)–(11)), annual available biomass to be processed (Eq. (12)), and non-negativity, binary, and integer constraints to guarantee a feasible solution (Eqs. (13)–(15)). Notations of model indices, parameters, and variables are given in the Nomenclature section.

$$\begin{aligned}\boldsymbol{MinTC} = &\sum_i \sum_j \sum_t F_c \times B_{ij} + (L_c + V_c) \times \frac{X_{ijt}}{U_c} \\ &+ \sum_i \sum_j \sum_t F_p \times B_{ij} + (L_p + V_p) \times \frac{X_{ijt}}{U_p}\end{aligned} \tag{1}$$

$$\begin{aligned}&+ \sum_j \sum_k \sum_t (F_m + L_m + V_m) \times \frac{X_{jkt}}{U_m} \\ &+ \sum_j \sum_l \sum_t (F_f + L_f + V_f) \times \frac{X_{jlt}}{U_f} \\ &+ \sum_i \sum_j \sum_t (F_{st} + L_{st} + V_{st}) \times \frac{X_{ijt}}{U_{st}}\end{aligned}$$

$$\begin{aligned}&+ \sum_j \sum_k \sum_t (F_{st} + L_{st} + V_{st}) \times \frac{X_{jkt}}{U_{st}} \\ &+ \sum_j \sum_l \sum_t (F_{dt} + L_{dt} + V_{dt}) \times \frac{X_{jlt}}{U_{dt}} \\ &+ \sum_k \sum_s \sum_t (F_{tt} + L_{tt} + V_{tt}) \times \frac{Y_{kst}}{U_{tt}}\end{aligned}$$

Subject To:

$$\sum_{i \in I} \sum_{t \in T} B_{ijt} \times \mu_{ijt} + (\sum_{i \in I} \sum_{t \in T} B_{ijt} \times \sigma_{ijt}^2)^{1/2} \times \varphi^{-1}(1-\alpha) \leqslant Q_t \quad \forall_i \in I, \quad \forall_t \in T \, \alpha \in [0,1] \tag{2}$$

$$\sum_{i \in I} \sum_{t \in T} B_{ijt} \times \mu_{ijt} + (\sum_{i \in I} \sum_{t \in T} B_{ijt} \times \sigma_{ijt}^2)^{1/2} \times \varphi^{-1}(1-\beta) \leqslant A_t \quad \forall_i \in I, \quad \forall_t \in T \, \beta \in [0,1] \tag{3}$$

$$X_{ijt} \leqslant Cap_i \times B_{ijt} \quad \forall_i \in I, \quad \forall_j \in J, \quad \forall_t \in T \tag{4}$$

$$\sum_{j \in J} \sum_{t \in T} X_{jkt} \leqslant Cap_m \quad \forall_j \in J, \quad \forall_t \in T \tag{5}$$

$$\sum_{j \in J} \sum_{t \in T} X_{jlt} \leqslant Cap_f \quad \forall_j \in J, \quad \forall_t \in T \tag{6}$$

$$\sum_{i \in I} \sum_{t \in T} B_{ijt} \leqslant N_t \quad \forall_i \in I, \quad \forall_t \in T \tag{7}$$

$$PY = Weight \times Q_t \quad \forall_t \in T \tag{8}$$

$$\sum_{i \in I} \sum_{t \in T} X_{ijt} - \sum_{l \in L} \sum_{t \in T} X_{jlt} - \sum_{j \in j} \sum_{t \in T} X_{jkt} = 0 \quad \forall_i \in I, \quad \forall_l \in L, \quad \forall_t \in T \tag{9}$$

$$PY \times \sum_{j \in j} \sum_{t \in T} X_{jkt} - \sum_{s \in S} \sum_{t \in T} Y_{kst} = 0 \qquad \forall_j \in J, \quad \forall_s \in S, \quad \forall_t \in T \tag{10}$$

$$PY \times \sum_{j \in J} \sum_{t \in T} X_{jlt} - \sum_{s \in S} \sum_{t \in T} Y_{lst} = 0 \quad \forall_j \in J, \quad \forall_s \in S, \quad \forall_t \in T \tag{11}$$

$$\sum_{i \in I} \sum_{j \in J} \sum_{t \in T} X_{ijt} \geqslant \theta_t \quad \forall_i \in I, \quad \forall_j \in J, \quad \forall_t \in T \tag{12}$$

$$X_{ijt}, X_{jkt}, X_{jlt} \geqslant 0 \quad for\ all\ i,j,k,l,\ and\ t \tag{13}$$

$$B_{ijt} = \{0,1\} \quad for\ all\ i,j\ and\ t \tag{14}$$

$$Y_{kst}, Y_{lst}\ are\ integers\ for\ all\ k,l,s,\ and\ t \tag{15}$$

2.2. Environmental impact analysis (Phase 2)

In addition to economic analysis in the proposed framework, environmental impact analysis is applied to evaluate the global warming potential (GWP) of the cost-effective supply chain network. The LCA method is used to assess environmental impacts over the bio-product (i.e., bio-oil and biochar) life cycle and includes four steps [57]: goal and scope definition, life cycle inventory (LCI), life cycle impact assessment (LCIA), and interpretation, which are described in Sections 2.2.1–2.2.4.

2.2.1. Goal and scope

Since utilization of bioenergy aims to alleviate environmental pressures, new bioenergy technologies need to be assessed in terms of their relative environmental impacts compared to conventional energy sources. The LCA study herein assesses GWP and applies a cradle-to-gate system boundary. The scope of this study includes two life cycle stages: upstream processing (i.e., biomass collection, staging, pre-processing, and transportation) and midstream processing (i.e., pretreatment and conversion to bio-oil) (Fig. 5). The functional unit selected in this study is one gallon of bio-oil produced under the scenario identified in Phase 1. The LCA is conducted using data and information from prior studies and LCA software, including SimaPro 8 (a commercial LCA tool from PRé Consultants) and GREET LCA 2016 (a freely-available tool from Argonne National Laboratory). LCA software packages are used to generate emissions factors for each entity in the BESC. GREET LCA 2016 provided data required for exploring collection and transportation environmental impacts. SimaPro 8 provided data for bio-oil production and bio-oil combustion impacts.

Table 2
Identified weights using the support vector machine technique (R Programming Results).

	Ash Content	Moisture Content	Quality Rate	Available Biomass	Distance to Staging Site	Accessibility Rate
Weight	15.9	28.5	33	57	54	32.8

Table 3
Testing dataset for collection sites.

Site No.	Average Ash Content (%)	Average Moisture Content (%)	Quality Rate (%)	Available Biomass (hundred tons)	Distance to Staging Site (miles)	Accessibility Rate (%)
11	3	6	6.5	12	13	5.5
12	3	5.5	7	15	11	7.5
13	3.5	5	7	12	14	6
14	2	5.5	8.5	13	10	7.5
15	3	6	7	15	9	8
16	3	6	7	12	10	6.8
17	3	6	7	14	15	7.5
18	2	6	7.5	12	10	6.8
19	3	5	8	12	13	5.5
20	3	6	6.5	15	11	7.5
Weight	15.5	28.5	34	61	54	33.4

2.2.2. Life cycle inventory

Equipment type and use characteristics are dependent upon the type of biomass utilized. The upstream forest biomass SC typically uses a forwarder, grinder, and loader. Upstream process inputs are biomass- and fossil-based energy (mainly diesel fuel) and lubricants, and the outputs are ground biomass (chips) and emissions from equipment operation. The GHG emission factor (in kg CO_2 eq. per metric ton of biomass) for the upstream biomass SC includes biomass collection and grinding. After collection and grinding, the chips are transferred to a bio-refinery, using different types of trucks with various capacities. Upstream processing inputs include chips and transportation fuel, and the outputs are transferred chips and emissions from fuel combustion. Factors such as biomass quality and moisture content have a direct effect on GWP. Transferring higher-quality, lower moisture content biomass can reduce the number of truck trips required to produce the same amount of bio-oil and, consequently, can reduce the environmental impacts of transportation. Travel distance and truck weight also directly affect fuel consumption.

In the midstream SC segment, biomass moisture content and particle size determine the type of pretreatment equipment and conversion technology used. The midstream SC input is feedstock (chips) and the outputs are biochar, syngas, bio-oil, and emissions. The emissions include steam released during chip drying and biogenic GHGs generated during bio-oil production when using biochar. Biochar and syngas for feedstock drying are funneled directly to the furnace (i.e., self-generated and closed-loop process). Biomass particle size and required process temperature play a key role in determining the pyrolysis type (e.g., fast, intermediate, or slow). Fast pyrolysis has a higher production yield (above 60%), but requires a high process temperature (500–900 °C) and smaller feedstock particle size (0.3–0.8 mm) [58]. Reducing the particles to the proper size requires more fossil-based energy (for grinding). The produced bio-oil will be transported to a distribution center by tanker truck, using diesel fuel as an input. Tanker truck trips and the distance from the bio-refinery to the distribution center are two major factors impacting fuel consumption. The number of trips has a direct relationship with the tanker truck capacity.

Table 4
Greenhouse Gas Emissions Factors for Biomass Collection and Bio-oil Production.

Substance	Biomass Collection (kg CO_2 eq. per metric ton of biomass)	Bio-oil Production (kg CO_2 eq. per metric ton of bio-oil)
CO_2 (Biogenic/ Fossil)	12.1	712
CH_4	0.612	None
N_2O	0.0448	585
Total	12.7	1300

GWP (in kg CO_2 equivalent) is calculated using GHG emissions factors for CH_4 (RCH_4) and N_2O (RN_2O), which are 72 kg CO_2 eq./kg CH_4 and 289 kg CO_2 eq./kg N_2O, respectively, as established by the Intergovernmental Panel on Climate Change (IPCC) for a 20-year time horizon [59]. Table 4 presents GHG emission factors for each substance from life cycle inventory databases in SimaPro 8 and GREET 2016 for biomass collection and bio-oil production.

2.2.3. Life cycle impact assessment

Environmental impact analysis was conducted using data (e.g., amount of biomass and distance) from a case study in the Pacific Northwest. The emissions factor (EF_{up}) environmental impacts (GWP, in kg CO_2 eq.) of the upstream segment (G_{up}) is calculated using Eqs. (16) and (17). Variables are defined in the Nomenclature.

$$EF_{up} = RCO_2 \times EF_{up}CO_2 + RCH_4 \times EF_{up}CH_4 + RN_2O \times EF_{up}N_2O \quad (16)$$

$$G_{up} = M_{mass} \times EF_{up} \quad (17)$$

The emissions factor (EF_{mass}) and GWP of biomass transportation (G_{mass}) are quantified using Eqs. (18) and (19).

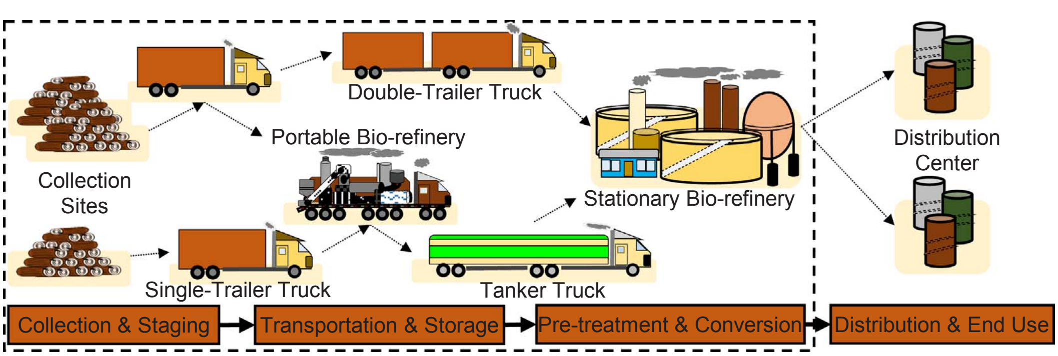

Fig. 5. Cradle-to-gate system boundary for bio-oil production (dotted line indicates the boundary).

$$EF_{mass} = RCO_2 \times EF_{mass}CO_2 + RCH_4 \times EF_{mass}CH_4 + RN_2O \times EF_{mass}N_2O \tag{18}$$

$$G_{mass} = M_{pro} \times EF_{mass} \times D \tag{19}$$

The emissions factor (EF_{pro}) and GWP of bio-oil production (G_{pro}), using a mobile or fixed bio-refinery, are calculated using Eqs. (20) and (21).

$$EF_{pro} = RCO_2 \times EF_{pro}CO_2 + RCH_4 \times EF_{pro}CH_4 + RN_2O \times EF_{pro}N_2O \tag{20}$$

$$G_{pro} = O_{pro} \times EF_{pro} \tag{21}$$

The emissions factor (EF_{oil}) and GWP of bio-oil transportation (G_{oil}) are quantified using Eqs. (22) and (23).

$$EF_{oil} = RCO_2 \times EF_{oil}CO_2 + RCH_4 \times EF_{oil}CH_4 + RN_2O \times EF_{oil}N_2O \tag{22}$$

$$G_{oil} = O_{pro} \times EF_{oil} \times D \tag{23}$$

2.2.4. Interpretation

The GHG emissions from biomass-based energy (e.g., bio-oil and biochar) combustion are classified as biogenic, or part of the natural cycle, and are absorbed by new, growing biomass [21]. Particulate emissions are negligible over all life cycle stages. GHG emissions of biomass, grinding, and transportation result from fossil fuel combustion, and are not considered as part of the natural carbon cycle [60]. Further details (issues identification and study evaluation) from the results of LCI and LCIA to conduct the interpretation step are given in Section 4 (Results and Discussion). A case study for biomass-based energy production is conducted in the next section to demonstrate the application of the proposed framework in the U.S. Pacific Northwest.

3. Case study

The case study presented here demonstrates the two-phase analysis approach presented above for conducting economic and environmental assessments of a BESC, while addressing several other limitations of prior work. In this study, mobile bio-refineries are located in close proximity to collection sites to address existing logistical challenges (e.g., low bulk density). Additionally, different road types are considered between collection sites and fixed bio-refineries, which along with the different processing modes, impact the types of trucks used in the SC. Actual data for the forest districts, available amounts and types of biomass, and locations of collection sites were obtained from ODF [61], which can be found in the Supplementary Materials. This data is used to reasonably demonstrate the application and verify the decision making method, mathematical models, and life cycle assessment.

The Base Case in the study considers twenty high-potential collection sites in three ODF forest districts, which are Forest Grove, Astoria, and Tillamook. These forest districts are scattered across Clatsop, Tillamook, Washington, and Columbia counties (Fig. 6) [62]. The main biomass types available are Douglas-fir (*Pseudotsuga menziesii*), western hemlock (*Tsuga heterophylla*), and red alder (*Alnus rubra*). The required equipment in the Base Case includes forwarders, grinders, single trailer trucks, double-trailer trucks, tanker trucks, and mobile bio-refinery units, as well as fixed bio-refinery facilities. Due to the high cost of using a lowboy to move the grinder and loader, the grinder is placed near the mobile bio-refinery or staging sites. In this study, the Base Case includes five staging sites, two mobile bio-refineries, and a fixed bio-refinery with storage capacity. Staging sites are considered to enable assembling of loads to take advantage of the maximum allowable legal weight. Fixed, variable, and labor costs are calculated using an approach reported by Brinker et al. [63]. The U.S. Producer Price Index is used to adjust cost values for inflation to 2016. To complete the analysis of the simulated supply chain (mobile bio-refineries are not currently in use by industry), the following assumptions were made based on real data or other information documented in the literature:

1. The capacities of mobile and fixed bio-refineries are 50 and 200 dry metric tons per day, respectively [22].
2. The annual scheduled production of a mobile bio-refinery is 329 days (12 h per day) [46].
3. The annual scheduled production of a fixed bio-refinery is 365 days (24 h per day) [22].
4. At least 20,000 metric tons of forest biomass (θ) is available at the twenty collection sites over a year time horizon.
5. The type of truck for each route is known.
6. The time horizon is one year.
7. Green wood has a 50% moisture content (wet basis) [21,55].
8. The higher heating value of bio-oil is 17.6 MJ/kg [64].
9. The total roundtrip distance from the storage facility to the end user is 150 miles (~241 km) [3].
10. The production yield for bio-oil conversion is 50% [22,65].
11. The quality rate is assumed to range from 0 to 5% for FHR of 50–60% moisture content [55].
12. The accessibility rate ranges from 0 to 5% for FHR with collection costs of $15–25/dry metric ton [26].
13. The effective lifetimes of mobile and fixed bio-refineries are assumed to be 10 and 12 years, respectively [66].

The roundtrip distances between the staging sites and mobile and fixed bio-refineries are defined with the assistance of GIS software (ArcGIS 10.1) using the shortest path method. Table 5 presents roundtrip distances, numbers of tractor-trailer and tanker truck trips,

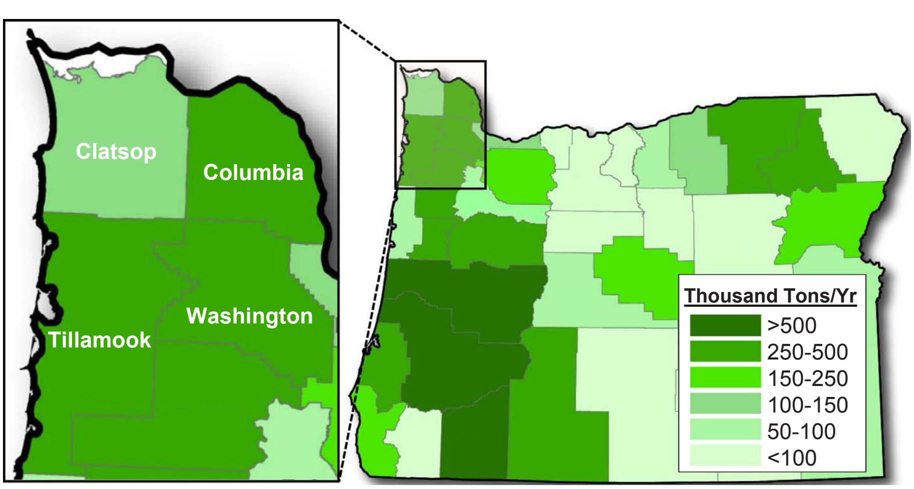

Fig. 6. Spatial distribution of forest biomass in the state of Oregon (Inset: Four Counties Considered in the Case Study) [62].

Table 5
Base case transportation details.

Pathway	Total Distance (miles)	Truck Trips	Tanker Trips	Truck Capacity (metric tons)	GWP (Mg CO_2 eq.)
C to PB	29,412	1,471	–	14	230.5
PB to FB	54,945	–	549	23	257.9
C to S	29,412	1,471	–	14	230.5
S to FB	86,957	870	–	25	864.6

C: Collection, PB/FB: Mobile/Fixed bio-refinery, S: Staging site.

and truck capacities for the upstream and midstream segments of the mixed SC, e.g., from collection sites to the mobile bio-refinery, and then to storage near the fixed bio-refinery, for the Base Case. In addition, the GWP associated with transportation for each pathway is reported.

The mean (μ) and variance (σ^2) of quality rate vs. q_{ij} and accessibility rate vs. α_{ij} are obtained from a simulated database for each staging site. The probabilities of the quality rate (α), average acceptable quality rate (Q), accessibility rate (β), and average acceptable accessibility rate (A) are calculated using the SVM algorithms and database described above. Since the probabilities are between 0 and 1, the α and β values are between 0 and 1. For instance, a particular site may produce biomass with an average quality rate of 60% and a variance of 4% (obtained from the simulated database). Staging sites with forest biomass attributes below the acceptable rates (A and Q) will not be considered by the algorithm because they do not meet the quality and accessibility constraints of the stochastic model.

A short-term storage facility is provided near the mobile bio-refinery, and associated costs are considered in the bio-refinery costs. The base number of collection sites (N) is 20 in this case study, meaning the decision maker chose to select the 20 collection sites (out of 50) with the highest biomass quality (i.e., lowest ash content or moisture content) and accessibility (i.e., biomass amount and shortest distance to staging site). The next section reports the results of our case study in the Pacific Northwest to demonstrate the decision making framework, and economic and environmental analyses.

4. Results and discussion

In the proposed mixed SC, the locations of mobile bio-refineries have been selected close to forest collection sites to reduce the number of truck trips needed to transport biomass feedstocks. Fewer truck trips not only reduce fuel consumption, but also mitigate GHG emissions and can aid bioenergy commercialization by lowering transportation costs. Traditionally, to reduce the number of truck trips, different types of trucks have been considered for in-forest roads and highways [1]. For instance, higher-capacity, double-trailer trucks can be used on main highways, while in-forest road travel is restricted to single-trailer trucks, which have more flexibility (e.g., in tight curves) and can turn around in smaller areas.

As discussed for Phase 1 (economic analysis), a mathematical model was formulated to assess the potential for bio-oil commercialization, using SVM and a stochastic optimization model. The obtained weight of each criterion via SVM can help decision makers to find the rate of quality (α) and accessibility (β), along with an average rate of quality (Q_t) and accessibility (A_t). In this study, Q_t and A_t are predicted at 75% and 70%, respectively, using R (a programming language for statistical computing). The proposed mathematical model is an NP-hard problem due to the binary decision variables. Thus, as the number of sites increases, decision making will become increasingly difficult (even impossible) without a proper computational algorithm. The major concern when developing an NP-hard problem is the solution approach and representation of the results. For instance, if the number of collection sites is 20, the number of solution combinations (either feasible or infeasible) will be 1,048,576 (2^{20}), which would lend itself to a heuristic or metaheuristic approach.

Using a GA, solved in MATLAB®, an optimal solution was found after 300 iterations in under six seconds using a system configured with a Windows 7, 64-bit Operating System, Intel Core i7 processor, and 8 GB RAM. The solution indicates that all available biomass would be processed in Collection Sites 1–20, producing approximately 10,000 metric tons (about 2.2 million gallons) of crude bio-oil over a one-year time horizon. The crude bio-oil would be produced via conventional pyrolysis (350–550 °C) with 50% production yield. The annual cost in the Base Case (mixed SC network) is predicted to be $2,387,595, resulting in a unit cost of $0.286/liter ($1.08/gallon). The solution for the mixed SC network indicated that the biomass would be processed using two mobile bio-refineries. The annual cost for the traditional SC network, without using mobile bio-refineries, is predicted as $2,957,327, resulting in a unit cost of $0.35/liter ($1.34/gallon). The optimal solutions obtained using the GA show a reasonable comparison to recently published costs (Table 6) for operations of similar size, i.e., $0.17–0.59/liter ($0.67–2.25/gallon) [1,22,67].

According to the results of a 2016 study conducted by Southern Research in cooperation with the U.S. DOE Bioenergy Technology Office (BETO), the predicted production cost (in 2013 dollars) of an HDO (hydrodeoxygenation) bio-oil was $0.82/liter ($3.10/gallon) for a current state-of-the-art (SOT) plant (capacity factor 75%), and $0.59/liter ($2.25/gallon) for a plant using future-target technology, or TARGET plant (capacity factor 90%) [71]. Additionally, the total net estimated GHG emissions potentials were reported as 72.6 and 69.4 kg CO_2 eq. per $MMBTU_{LHV}$ (10.9 and 10.4 kg CO_2 eq. per gallon of bio-oil) for the SOT Plant and TARGET Plant, respectively, when assuming no indirect land use change [71]. In this study, we considered the impacts of CO_2, CH_4, and N_2O emissions of the bio-oil using a 20-year global warming potentials for determining carbon dioxide equivalents. The Southern Research study additionally considered SF_6 emissions and used 100-year global warming potentials in determining carbon dioxide equivalents. Also, while our study considered pyrolysis conversion technology for forest biomass (i.e., Douglas-fir, western hemlock, and

Table 6
Predicted bio-oil production cost reported in recent studies.

Research Overview	Year	Refinery size (metric ton/day)	Bio-oil production cost ($/gal)	Study
Fast pyrolysis to convert southern pine wood chips	2010	100	0.94	[22]
Fast pyrolysis to convert woody biomass	2011	2000	0.60	[68]
Fast pyrolysis to convert woody biomass	2012	2000	0.59	[68]
Mobile pyrolysis to convert forest residues	2013	15	1.76	[67]
Purchased bio-oil at $236/ton including $76/ton biomass cost	2014	–	0.78	[69]
Conventional mobile pyrolysis to convert forest biomass	2015	13.6	1.15	[26]
Catalytic pyrolysis to convert woody biomass	2016	500	2.05	[70]
This study	2017	50	1.34	–
Liquefaction and hydrodeoxygenation to convert southern pine[a]	2016	1240	2.25	[71]
Fuel Oil No. 6 (July 2017)	2017	–	1.17	[72]

[a] TARGET Plant with 90% capacity.

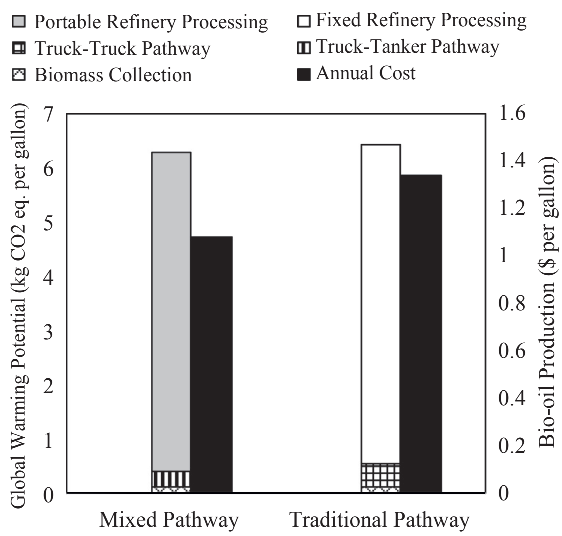

Fig. 7. Cradle-to-gate global warming potential for bio-oil production and annual cost.

red alder), the Southern Research study considered a thermal liquefaction conversion process for southern pine plantation biomass.

Both traditional and mixed pathways use similar equipment for biomass collection, bio-refinery processing, and bio-oil combustion. Further, the GHG emissions resulting from these activities are similar for both pathways. For instance, the fixed and mobile bio-refineries both employ conventional pyrolysis technology for crude bio-oil production, where the GHG emission rate is predicted to be 1.3 Mg CO_2 eq. per metric ton of bio-oil. Consequently, the environmental impact (GWP) of a bio-refinery producing approximately 10,000 metric tons of bio-oil from 20,000 metric tons of biomass is 13,000 Mg CO_2 eq. Since it is assumed biochar and syngas are used as an energy source, releasing biogenic CO_2, bio-refinery processing GHG emissions are considered negligible [21]. Additionally, the GHG emissions rate for biomass collection and bio-oil combustion is predicted as 0.12 kg CO_2 eq. per metric ton of bio-oil and 18.7 kg CO_2 eq. per metric ton of bio-oil, respectively, for both pathways.

Fig. 7 indicates the GWP for each life cycle stage associated with crude bio-oil production. The key difference between the traditional and mixed pathway is due to the number of truck and truck-tanker trips between the collection sites and fixed bio-refinery (also the bio-oil storage location). The GHG emissions of transportation in the Base Case, using the truck-tanker pathway, is 0.29 kg CO_2 eq. per gallon of bio-oil, while the truck-truck pathway is 0.43 kg CO_2 eq. per gallon of bio-oil. In the Base Case, when considering the cradle-to-gate processes (i.e., biomass collection, grinding, transportation and bio-refinery processing), the net GHG emissions for crude bio-oil is predicted as 13.8 Mg CO_2 eq. (6.29 kg CO_2 eq. per gallon of bio-oil) using a mobile bio-refinery and truck-tanker pathway (mixed), and 14.17 Mg CO_2 eq. (6.43 kg CO_2 eq. per gallon of bio-oil) using fixed bio-refinery and truck-truck pathway (traditional) (Fig. 8). Thus, the mixed pathway (Base Case) reduces GWP by 318 Mg CO_2 eq. per year (0.14 kg CO_2 eq. per gallon). It can be seen that emissions of CO_2 are greater than other GHG emissions for each phase of the bio-oil life cycle.

There are several threats to validity that should be considered when considering the results obtained in this study. The primary threat to the validity is whether the approach developed and applied can sufficiently address the problem identified at the outset of the study, which aimed to determine if the mixed SC could enhance the economic and environmental benefits for bio-oil production from biomass. To address this concern, the results of the study have been compared with similar published studies to judge their accuracy. It was found that the results of this study compare well to other recent studies. The threat to internal validity (how well the study is done) of this study relates to maturation (physical or psychological changes), since biomass has variable physical characteristics depending on time and location of collection, handling practices, and other factors. Other threats to internal validity (e.g., statistical analysis, history effect, testing, morality, and instrumentation) are not directly related to the approach pursued in this study [73,74]. Key threats to external validity (validity of generalized inferences in research) of this study are that specific findings cannot be guaranteed to be appropriate to regions outside of the scope of this study [75]. It is hoped, however, that this study can provide general recommendations that are helpful for studies in other regions.

4.1. Sensitivity analysis

Based on the structure of the optimization model, several parameters have significant effects on the economic and environmental performance of the system, which can be examined using sensitivity analysis. The purpose of sensitivity analysis is to explore the effect of variables (e.g., binary, continuous, and integer variables) and right hand side parameters (e.g., capacity) on the cost optimization results. This section presents a sensitivity analysis to assess the effect of the main parameters, such as available amount biomass and mobile bio-refinery cost. Apart from the Base Case, two different cases are presented below, which explore the sensitivity of the results to these two parameters (arbitrarily ± 50%).

4.1.1. Effect of mobile bio-refinery cost

Mobile bio-refinery costs are the major driver of bio-oil production cost in the Base Case. Thus, since mobile bio-refinery technology remains in development, exploring the effect of this attribute is essential to assess the commercial feasibility of bioenergy production. In the first alternative case (Case 1), mobile bio-refinery costs (i.e., fixed, variable, and labor costs) are reduced by 50%. In the second case (Case 2), mobile bio-refinery costs are increased by 50%. Table 7 reports the cost

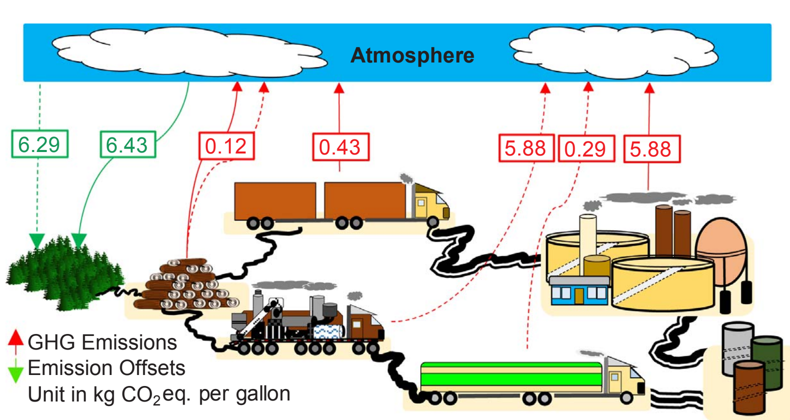

Fig. 8. Carbon balance for the crude bio-oil production (solid and dashed lines indicate traditional and mixed pathways, respectively).

Table 7
Effect of mobile bio-refinery cost on the overall annual cost.

Cases	Annual Overall Cost ($)	Annual Bio-refinery Cost ($/yr.)		
		Fixed Cost	Variable Cost	Labor Cost
Base Case	2,387,595	600,762	89,082	375,357
Case 0[a]	2,957,327	4,314,095	1,578,218	1,155,334
Case 1 (−50% cost)	1,739,071	300,381	44,541	187,678
Case 2 (+50% cost)	2,957,327	4,314,095	1,578,218	1,155,334

[a] Base Case without mobile bio-refinery.

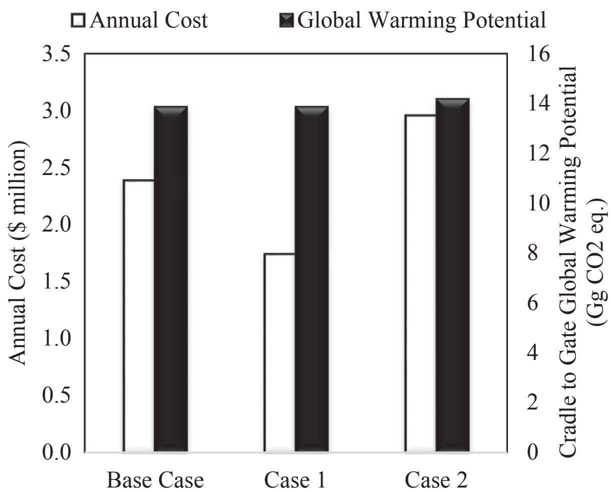

Fig. 9. Effect of portable bio-refinery cost on environmental and economic measures.

optimal results for each case and the results without the mobile bio-refinery (Base Case).

The results indicate that changes in mobile bio-refinery costs significantly impact the total cost, while also changing the configuration of the optimal supply chain. The overall annual cost decreased in Case 1 by approximately $648,524 (−27%) and in Case 2, the annual cost increased by $569,732 (+23%). Case 1 also indicates that the cost optimal supply chain would utilize two mobile bio-refineries. In Case 2, however, the fixed bio-refinery would be responsible for processing all forest biomass due to higher costs of production, transportation, and storage when using the higher-cost mobile bio-refinery (Fig. 9). Although the bio-refinery costs are higher in Case 2, the increased processing rate of using the fixed bio-refinery otherwise reduces total annual cost. While transportation cost of the traditional pathway is higher than the mixed pathway, the combination of single- and double-trailer trucks in the traditional pathway reduces the transportation costs compared to using only single-trailer trucks. Since the amount of processed biomass and the number and location of bio-refineries remains constant, the GWP remains the same as Base Case and Case 0 for Case 1 and Case 2, respectively.

4.1.2. Effect of available amount of forest biomass

The amount of available biomass in the Base Case is based on the remaining non-merchantable products at the forest roadside (assumed to be 20,000 metric tons), which is not the only potential source of biomass for bio-oil production at the sites considered. Other sources include branches, tops, and breakage, equating to an additional 30,000 metric tons for the area considered, according to ODF, which are mainly burned due to high collection costs. The effect of the available amount of forest biomass is also investigated due to the importance of this attribute in the proposed method. In Phase 1, the available amount of biomass is the main parameter, along with biomass quality. Therefore,

Table 8
Effect of available amount of forest biomass on the associated cost and environmental impact.

Cases	Amount of Biomass (metric ton)	Bio-oil Production ($/gallon)	GWP (kg CO_2 eq. per gallon)
Base Case	20,000	1.08	6.28
Case 3 (−50% amount of biomass)	10,000	1.53	6.41
Case 4 (+50% amount of biomass)	30,000	1.33	6.24

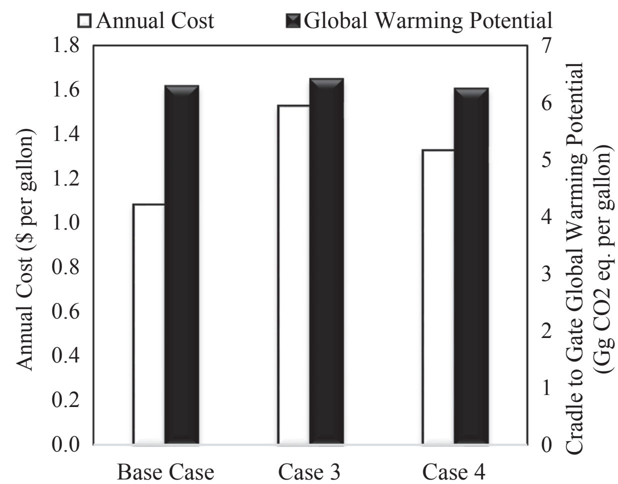

Fig. 10. Effect of the available amount of forest biomass on environmental and economic measures.

changing the amount of available biomass affects the total annual cost of the simulated network, due to the direct impacts of these parameters on each entity in the BESC. In Case 3, the available amount is decreased by 50%. In Case 4, the available amount is increased by 50%. Changing the amount of biomass has a direct impact on collection, pre-processing, transportation, and bio-refinery costs. Table 8 reports the predicted cost and environmental impact for each case.

The total SC cost is found to change directly, but nonlinearly, with the amount of available biomass processed. In Cases 3 and 4, the bio-oil cost per gallon increased by 41% and 22%, respectively. The optimal SCs utilize one mobile bio-refinery in Case 3, and two mobile bio-refineries in Case 4. The effect of biomass availability on the various components of SC costs are shown in Fig. 10. Added biomass would increase the environmental impacts of biomass collection, size reduction, and transport. Since the upstream activities mainly use fossil energy, the emissions released during these activities negatively affect environmental performance. The results indicate that GWP is increased by 0.12 kg CO_2 eq. per gallon for Case 3 and reduced by 0.04 kg CO_2 eq. per gallon for Case 4, compared to the Base Case.

5. Conclusions

The sustainable management of available biomass feedstocks represents an urgent societal need that is not being met due to uncertain economic and environmental conditions across BESCs. There are two primary deficiencies of prior studies that were addressed in this study: (a) consideration of upstream uncertainties in BESC modeling and (b) development of a multi-criteria decision making framework and reliable computational methods to facilitate the identification of sustainable BESC networks. These deficiencies can be overcome with the development and application of integrated decision support systems, as explored herein. Prior studies inconsistently addressed the triple bottom line (i.e., economic, environmental, and social performance) and associated uncertainties in the BESCs. This research evaluated the objectives of cost and environmental impact, along with assessing the role of network uncertainties, mixed-mode bio-refineries, and mixed-pathway transportation, in order to support broader bioenergy commercialization. As such, the resulting multi-criteria decision making framework couples sustainability ideology and technological aspects of bio-oil production to an extent not done previously.

The motivation behind the BESC framework lies in inherent limitations of existing bioenergy production methods. Decision makers (e.g., policy makers and supply chain managers) will benefit from integration of resources, technologies, and processes within the proposed framework that will enhance the sustainability performance of the energy industry. The results indicate the proposed mixed supply chain can enhance the sustainability performance of bio-oil production by reducing the cost and environmental impacts. This research motivates a need for technology development (e.g., integrating distributed and centralized bio-refineries) and implementation for integrating the reliable pretreatment process into the upstream segment of BESCs, incorporating upstream uncertainty sources, evaluating investment factors, and comparing different system designs and assumptions. By taking advantage of ongoing work in supply chain and process technology development, as well as mathematical modeling and optimization, viable commercial approaches will emerge to scale up bioenergy production and support a sustainable bioenergy industry. The potential paths for future research include (a) exploration of all BESC segments (i.e., upstream, midstream, and downstream) to identify technological, economic, and policy challenges and (b) exploration of a multiple-year, rather than one-year, time horizon to evaluate broader economic and environmental impacts, such as soil organic carbon changes and carbon cycling, and (c) exploration of workforce development and social benefits associated with biodiversity enhancement, such as water, habitat, and land availability.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2017.09.001.

References

[1] Mirkouei A, Haapala KR, Sessions J, Murthy GS. A review and future directions in techno-economic modeling and optimization of upstream forest biomass to bio-oil supply chains. Renew Sustain Energy Rev 2017;67:15–35.
[2] Yang Y, Brammer JG, Wright DG, Scott JA, Serrano C, Bridgwater AV. Combined heat and power from the intermediate pyrolysis of biomass materials: performance, economics and environmental impact. Appl Energy 2017;191:639–52.
[3] Perlack RD et al., US billion-ton update: biomass supply for a bioenergy and bioproducts industry, 2011.
[4] Chiaramonti D, Prussi M, Buffi M, Rizzo AM, Pari L. Review and experimental study on pyrolysis and hydrothermal liquefaction of microalgae for biofuel production. Appl Energy 2017;185:963–72.
[5] U.S. DOE, 2016 Billion-Ton Report | Department of Energy; 2016. Available: < http://energy.gov/eere/bioenergy/2016-billion-ton-report > .
[6] U.S. EIA, Annual Energy Outlook 2015 – Energy Information Administration; 2015. Available: < http://www.eia.gov/forecasts/aeo/ > [accessed: 26-Jan-2016].
[7] DOE, Climate Change | Department of Energy; 2016. Available: < http://energy.gov/science-innovation/climate-change > .
[8] U.S. DOE, U.S. Billion-Ton Update – Summary Findings; 2011.
[9] U.S. DOE, Our Commitment to Bioenergy Sustainability; 2011.
[10] Patel M, Zhang X, Kumar A. Techno-economic and life cycle assessment on lignocellulosic biomass thermochemical conversion technologies: a review. Renew Sustain Energy Rev 2016;53:1486–99.
[11] Jaroenkhasemmeesuk C, Tippayawong N. Technical and economic analysis of a biomass pyrolysis plant. Energy Procedia 2015;79:950–5.
[12] Awudu I, Zhang J. Uncertainties and sustainability concepts in biofuel supply chain management: a review. Renew Sustain Energy Rev 2012;16(2):1359–68.
[13] Yue D, You F, Snyder SW. Biomass-to-bioenergy and biofuel supply chain optimization: overview, key issues and challenges. Comput Chem Eng 2014;66:36–56.
[14] de Jong S, Hoefnagels R, Wetterlund E, Pettersson K, Faaij A, Junginger M. Cost optimization of biofuel production – the impact of scale, integration, transport and supply chain configurations. Appl Energy 2017;195:1055–70.
[15] Lim CH, Lam HL. Biomass supply chain optimisation via novel Biomass Element Life Cycle Analysis (BELCA). Appl Energy 2016;161:733–45.
[16] Elliott DC, Beckman D, Bridgwater AV, Diebold JP, Gevert SB, Solantausta Y. Developments in direct thermochemical liquefaction of biomass: 1983–1990. Energy Fuels 1991;5(3):399–410.
[17] Solantausta Y, Beckman D, Bridgwater AV, Diebold JP, Elliott DC. Assessment of liquefaction and pyrolysis systems. Biomass Bioenergy 1992;2(1):279–97.
[18] Mitchell CP, Bridgwater AV, Stevens DJ, Toft AJ, Watters MP. Technoeconomic assessment of biomass to energy. Biomass Bioenergy 1995;9(1–5):205–26.
[19] De Jong S, Hoefnagels R, Faaij A, Slade R, Mawhood R, Junginger M. The feasibility of short-term production strategies for renewable jet fuels–a comprehensive techno-economic comparison. Biofuels Bioprod. Biorefining 2015;9(6):778–800.
[20] Alves CM, Valk M, de Jong S, Bonomi A, van der Wielen LAM, Mussatto SI. Techno-economic assessment of biorefinery technologies for aviation biofuels supply chains in Brazil. Biofuels Bioprod. Biorefining 2017;11(1):67–91.
[21] Steele P, Puettmann ME, Kanthi Penmetsa V, Cooper JE. Life-cycle assessment of pyrolysis bio-oil production. For Prod J 2012;62(4):326.
[22] Badger P, Badger S, Puettmann M, Steele P, Cooper J. Techno-economic analysis: preliminary assessment of pyrolysis oil production costs and material energy balance associated with a transportable fast pyrolysis system. BioResources 2010;6(1):34–47.
[23] Zhang F, Wang J, Liu S, Zhang S, Sutherland JW. Integrating GIS with optimization method for a biofuel feedstock supply chain. Biomass Bioenergy 2017;98:194–205.
[24] Zamora-Cristales R, Boston K, Sessions J, Murphy G. "Stochastic simulation and optimization of mobile chipping economics in processing and transport of forest biomass from residues. Silva Fenn 2014;47(5).
[25] Zhang F, Johnson D, Johnson M, Watkins D, Froese R, Wang J. Decision support system integrating GIS with simulation and optimisation for a biofuel supply chain. Renew Energy 2016;85:740–8.
[26] Mirkouei A, Mirzaie P, Haapala KR, Sessions J, Murthy GS. Reducing the cost and environmental impact of integrated fixed and mobile bio-oil refinery supply chains. J Clean Prod 2015.
[27] Awudu I, Zhang J. Stochastic production planning for a biofuel supply chain under demand and price uncertainties. Appl Energy 2013;103:189–96.
[28] Cambero C, Sowlati T. Incorporating social benefits in multi-objective optimization of forest-based bioenergy and biofuel supply chains. Appl Energy 2016;178:721–35.
[29] Ba BH, Prins C, Prodhon C. Models for optimization and performance evaluation of biomass supply chains: an operations research perspective. Renew Energy 2016;87:977–89.
[30] Mirkouei A, Haapala KR, Sessions J, Murthy GS. Evolutionary optimization of bioenergy supply chain cost with uncertain forest biomass quality and availability. In: Proceedings of the IIE-ISERC, May 21–24, Anaheim, California, USA; 2016.
[31] 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(Part 4):3285–93.
[32] Schmidt J. D. für W. S. U. für B. Wien. Using Monte Carlo simultation to account for uncertainties in the spatial explicit modeling of biomass fired combined heat and power potentials in Austria. Univ. für Bodenkultur, Department für Wirtschafts-und Sozialwiss., Inst. für Nachhaltige Wirtschaftsentwicklung; 2009.
[33] Mirkouei A. Techno-economic optimization and environmental impact analysis for a mixed-mode upstream and midstream forest biomass to bio-products supply chain. Oregon State University; 2016.
[34] Meyer S. US biofuels analysis under uncertainty and volatility in the biofuels industry: FAPRI stochastic modeling Presented at 'Biofuels, Food and Feed Tradeoffs' Farm Foundation, 12–13 April 2007; 2007.
[35] Gebreslassie BH, Yao Y, You F. Design under uncertainty of hydrocarbon biorefinery supply chains: multiobjective stochastic programming models, decomposition algorithm, and a Comparison between CVaR and downside risk. AIChE J 2012;58(7):2155–79.
[36] Kim J, Realff MJ, Lee JH, Whittaker C, Furtner L. Design of biomass processing network for biofuel production using an milp model. Biomass Bioenergy 2011;35(2):853–71.
[37] Rozakis S, Sourie J-C. Micro-economic modelling of biofuel system in France to determine tax exemption policy under uncertainty. Energy Policy 2005;33(2):171–82.
[38] Deb K. Multi-objective optimization,. Search methodologies. Springer; 2014. p. 403–49.
[39] 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.
[40] Jellouli O, Chatelet E. Monte Carlo simulation and genetic algorithm for optimising supply chain management in a stochastic environment. In: Systems, man, and cybernetics, 2001 IEEE international conference on, vol. 3; 2001. p. 1835–9.
[41] Quiza Sardiñas R, Rivas Santana M, Alfonso Brindis E. Genetic algorithm-based multi-objective optimization of cutting parameters in turning processes. Eng Appl

Artif Intell 2006;19(2):127–33.
[42] Yue D, Pandya S, You F. Integrating hybrid life cycle assessment with multi-objective optimization: a modeling framework. Environ Sci Technol 2016.
[43] Lattimore B, Smith CT, Titus BD, Stupak I, Egnell G. Environmental factors in woodfuel production: opportunities, risks, and criteria and indicators for sustainable practices. Biomass Bioenergy 2009;33(10):1321–42.
[44] Walker T, et al. Biomass sustainability and carbon policy study. Manomet Cent Conserv Sci 2010.
[45] Thornley P, Gilbert P, Shackley S, Hammond J. Maximizing the greenhouse gas reductions from biomass: the role of life cycle assessment. Biomass Bioenergy 2015;81:35–43.
[46] Sorenson CB. A comparative financial analysis of fast pyrolysis plants in southwest oregon. MT: The University of Montana Missoula; 2010.
[47] Lim CH, Mohammed IY, Abakr YA, Kazi FK, Yusup S, Lam HL. Novel input-output prediction approach for biomass pyrolysis. J Clean Prod 2016;136:51–61.
[48] Sadaka S, Boateng AA, et al. Pyrolysis and bio-oil [Cooperative Extension Service]. University of Arkansas, US Department of Agriculture and County Governments Cooperating; 2009.
[49] Union of Concerned Scientists. The promise of biomass clean power and fuel – if handled right; 2012. Available: < http://www.ucsusa.org > .
[50] Cristianini N, Shawe-Taylor J. An introduction to support vector machines and other kernel-based learning methods. Cambridge University Press; 2000.
[51] Shawe-Taylor J, Cristianini N. Kernel methods for pattern analysis. Cambridge University Press; 2004.
[52] Esen H, Inalli M, Sengur A, Esen M. Modeling a ground-coupled heat pump system by a support vector machine. Renew Energy 2008;33(8):1814–23.
[53] Esen H, Ozgen F, Esen M, Sengur A. Modelling of a new solar air heater through least-squares support vector machines. Expert Syst Appl 2009;36(7):10673–82.
[54] Northwest Advanced Renewables Alliance. Variations of Forest Residual Biomass; 2014.
[55] Thiffault E, Smith CT, Junginger M, Berndes G. Mobilisation of forest bioenergy in the boreal and temperate biomes: challenges, opportunities and case studies. Academic Press; 2016.
[56] Karatzoglou A, Meyer D, Hornik K. Support vector machines in R; 2005.
[57] Curran MA. Life cycle assessment: principles and practice, EPA/600/R-06/060. U.S. Environmental Protection Agency, Cincinnati, OH, EPA/600/R-06/060; May 2006.
[58] Septien S, Valin S, Dupont C, Peyrot M, Salvador S. Effect of particle size and temperature on woody biomass fast pyrolysis at high temperature (1000–1400 C). Fuel 2012;97:202–10.
[59] IPCC. 2.10.2 Direct Global Warming Potentials – AR4 WGI Chapter 2: Changes in Atmospheric Constituents and in Radiative Forcing; 2007.
[60] Johnson L, Lippke B, Oneil E. Modeling biomass collection and woods processing life-cycle analysis. For Prod J 2012;62(4):258–72.
[61] ODF. State of Oregon: Oregon Department of Forestry – Home; 2015. Available: < http://www.oregon.gov/odf/Pages/index.aspx > [accessed: 12-Oct-2015].
[62] U.S. DOE. National Renewable Energy Laboratory, The Biofuels Atlas; 2017.
[63] Brinker RW, Miller D, Stokes BJ, Lanford BL. Machine rates for selected forest harvesting machines. Circ. 296 Revis. Ala. Agric Exp Stn. Auburn Univ 2002;32.
[64] Dynamotive. Dynamotive Energy Systems Corporation, Canadian BioOil Plant: Summary (USD); 2009.
[65] Bridgwater AV. Review of fast pyrolysis of biomass and product upgrading. Biomass Bioenergy 2012.
[66] Page-Dumroese D et al. Portable in-woods pyrolysis: using forest biomass to reduce forest fuels, increase soil productivity, and sequester carbon. In: Proceedings of the 2009 North American biochar conference; 2009. < http://cees.colorado.edu/biochar_production.html > [accessed 05 01 10].
[67] Brown D, Rowe A, Wild P. A techno-economic analysis of using mobile distributed pyrolysis facilities to deliver a forest residue resource. Bioresour Technol 2013;150:367–76.
[68] Jones SB, Male JL. Production of gasoline and diesel from biomass via fast pyrolysis, hydrotreating and hydrocracking: 2011 state of technology and projections to 2017. Pacific Northwest National Laboratory; 2012.
[69] Czernik S, French R. Distributed production of hydrogen by auto-thermal reforming of fast pyrolysis bio-oil. Int J Hydrog Energy 2014;39(2):744–50.
[70] Vasalos IA, Lappas AA, Kopalidou EP, Kalogiannis KG. Biomass catalytic pyrolysis: process design and economic analysis. Wiley Interdiscip Rev Energy Environ 2016;5(3):370–83.
[71] Gangwal S, Meng J, McCabe K, Larson E, Mastro K. Mild biomass liquefaction process for economic production of stabilized refinery-ready bio-oil, southern research, Durham, NC (United States), DOE-Southern Research—0006062; Apr. 2016.
[72] U.S. EIA. Short-Term Energy Outlook – U.S. Energy Information Administration (EIA); 2017. Available: < https://www.eia.gov/outlooks/steo/ > [accessed: 26-Jul-2017].
[73] Anderke S. Improving the bioethanol sector in GermanyFrance and Spain BS. thesis University of Twente; 2013.
[74] Gerring J. Social science methodology: a unified framework. Cambridge University Press; 2011.
[75] Babbie ER. The practice of social research. Nelson Education; 2015.