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A hybrid machine learning solution for redesigning sustainable circular energy supply chains

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ABSTRACT

Sustainability development goals require decision-makers to incorporate social and environmental indicators in their economic models using innovative solutions, such as a sustainable circular economy. This paper presents an innovative integrated production and logistic model for a circular economy using multi-objective optimization. Empirical data includes a renewable energy supply chain. We assess the sustainability performance of the proposed decision-making model by simultaneously considering production and logistics costs, carbon emissions, and the number of jobs created. The case study is optimized with an exact method, and a hybrid machine-learning algorithm solves large-scale numerical examples. The paper's main contributions include movable manufacturers, uncertain parameters, a hybrid machine learning algorithm, and empirical data in the proposed decision-making model. The findings show that a moveable facility can substantially decrease total cost and carbon emissions. Sensitivity analysis shows that changes in moveable capacity and percent yield considerably impact the objectives. Findings show that decision-makers can achieve cost parity with fossil-based sources when employing circular supply chain management.

1. Introduction

Climate change significantly impacts countries. The increase in the global population highlights the importance of efficiency in sustainability programs, particularly in cleaner production to achieve net zero emissions (Habibi et al., 2023). Sustainable biofuel logistics and production involve managing the flow of materials while addressing the sustainability pillars: society, environment, and economy (Jabbour et al., 2020). Sustainable assessments can help decision-makers include environmental and societal concerns in their cost-based decision-making models by including circular economy transitions (Saccani et al., 2023). This paper proposes a sustainable biofuel supply chain that includes the circular approach of a renewable energy network in which biomass is used to produce biofuel.

Through innovative production and logistics decision-making models, biofuel supply chains not only reduce wildfire dangers but also benefit the environment and economy by utilizing underexploited forest resources (Madrigal et al., 2017) and decreasing fossil fuel dependency. Therefore, promoting innovative sustainable solutions, such as the circular economy (Acerbi et al., 2022), is essential part of strategies to mitigate environmental risks and to approach achieving net-zero policy (Elia et al., 2020). However, technical and organizational challenges slow net-zero practices (Bressanelli et al., 2019).

Past works have addressed the principles of biofuel production, including biomass transportation optimization (Habibi et al., 2023), modeling approaches (Quddus et al., 2018), and flexible production (Mridha et al., 2023). However, meeting holistic sustainability goals has not been a focus of biofuel development and evaluation (Santos et al., 2019). Few studies in mobile biofuel production have included innovative integrated production and logistic models, such as circular supply chain management. The circular economy can significantly impact continuous flows throughout the product lifecycle (Sassanelli et al., 2023). In a circular supply chain, previously utilized products or components undergo a return or processing procedure, which facilitates their resale or recycling (Bressanelli et al., 2022). Additionally, more work is needed to incorporate machine learning optimization in renewable energy models, including the circular economy approach for optimizing large-scale problems. Therefore, the research question is:

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How does circular supply chain management influence decision-making models in renewable energy?

To address this research gap, this paper proposes an innovative integrated production and logistic model for a circular economy in energy supply chains. The presented mathematical model optimizes the three pillars of sustainability in bio-energy supply chains. This paper combines exact methods for a case study and a hybrid machine learning algorithm for large-scale numerical examples to ensure the rigor and practicality of the proposed solution.

This research contributes to past work by addressing the following issues. First, the quantification of job creation has not been captured as a decision-making variable within mobile refinery-dependent transportation networks under uncertain input conditions. Second, there has been a lack of optimization for the carbon footprint as a variable in transportation networks involving a combination of different refinery types under uncertain scenarios. Third, the consideration of operating costs per product has been absent in the analysis of mixed biofuel challenges where conditions are not clearly defined. Fourth, the integration of circular supply chain management within renewable energy decision-making models has not been comprehensively addressed (Farooque et al., 2019; Lahane et al., 2020; Rosa et al., 2020). Last but not least, the development and optimization of a combined machine learning algorithm designed for multi-objective models in the context of mixed-refinery biofuel transportation issues have not been thoroughly explored (Habibi et al., 2023).

This paper presents several theoretical advancements in circular bioenergy supply chains. First, this paper introduces a multi-objective optimization model that simultaneously captures the three pillars of sustainability, which is a necessary step toward equitable consideration of societal indicators previously evaluated solely in terms of cost. For instance, while traditional models focus solely on optimizing costs, multi-objective models provide a hazard-free environment for port workers. The second advancement involves combining environmental and societal factors into economic models, which have received insufficient attention in past economic decision-making models. Third, this paper recognizes the importance of addressing uncertainty and ambiguity in sustainable decision-making models. Last but not least, this paper contributes two significant theoretical advancements to circular supply chain problems: a hybrid solution algorithm and theoretical validation through a case study in northwest Oregon. The corresponding code is publicly accessible on www.github.com/naricode/CAIE2024, encouraging academic contribution to this field.

This paper introduces several practical advancements. First, the suggested bioenergy supply chains can reduce wildfire risk and dependence on fossil fuels. Mobile refineries have the potential to shift the economics of production to facilitate the processing of distributed forest biomass. Second, the proposed movable manufacturing units can enhance resource utilization in energy supply chain management through the dynamic relocation of production and logistics facilities. Third, the empirical data used in this paper supports the model's applications under real-world conditions, thereby increasing the model's accuracy and relevance. Fourth, the proposed circular approach in bioenergy supply chains can increase profitability while promoting sustainable development. Last but not least, operational efficiencies in real-time can be improved through the proposed machine learning-based optimization.

This paper continues with the next section, which reviews the related works. Sections 3 and 4 provide the method and results of a case study. Section 5 presents a hybrid machine learning algorithm for large-scale problems of circular supply chain models. Finally, Section 6 presents the discussion, conclusion, and opportunities for future research.

2. Prior related work

Past works provided a review of prior studies in biofuel production technologies (Prasad et al., 2024), bio-hubs (Valipour et al., 2024), risk in bioenergy supply chains (Axon & Darton, 2024), emerging technologies in sustainable production (Sharmila et al., 2024), logistics in bioenergy (Balanay & Halog, 2024), collaboration in circular economy (Sudusinghe & Seuring, 2022), circular economy goals (Gupta & Singh, 2024), circular economy benefits (Pan et al., 2024), industry 4.0 in circular economy (Taddei et al., 2022), circular economy methods (Sassanelli et al., 2019), and metaheuristics optimization (Martí et al., 2024), which can provide a detail of concepts for interested readers.

2.1. Bioenergy supply chain

Biomass is recognized as an environmentally friendly energy source, and sustainable energy systems based on biomass feedstocks can enhance societal welfare. Pérez-Fortes et al. (2012) were among the first to report on the societal effects of sustainable transportation on job creation and the environment. Their model, which considered biomass sourcing, pretreatment, electricity generation, and distribution, employed the ε-constraint method for optimization. Further studies have expanded on societal impacts in supply chain management. Ramos et al. (2014) examined the role of societal and environmental impacts in recyclable waste collection chains, which focused on working hours and carbon footprint. For the Canadian lumber industry, Boukherroub et al. (2015) proposed wealth and job creation indicators in their mathematical model, and then they employed a weighted goal-programming algorithm to optimize it. In the consideration of effects of inventory systems on the environment, Zhang et al. (2014) presented a multi-objective framework by which they optimized lead time. Moreover, Cambero and Sowlati (2016) evaluated the role of bioenergy supply chains in increasing job opportunities in which they employed the augmented ε-constraint method for the optimization. In addition, Osmani and Zhang (2017) employed the Benders decomposition algorithm to solve a biomass supply chain in Wisconsin.

When it comes to biomass resources, global supply chain management is inevitable due to logistics advantages in international markets. In doing so, Mauro et al. (2018) developed an international biomass supply chain for optimizing their carbon emissions and logistics costs. Their findings revealed the considerable impacts of pretreatment technologies on supply chain outcomes. Akgül and Seçkiner (2019) optimized a bioenergy supply chain in Turkey for maximizing total profit and minimizing operational costs. Their proposed model improves rural areas with bio-based businesses. Wang et al. (2022) developed a multiperiod model for biofuel supply chains in China, which was solved by the game theory. Mridha et al. (2023) suggested a flexible production for smart, sustainable supply chains to optimize energy usage and carbon emissions. Yunusoglu et al. (2024) developed a location model for including obnoxious facilities in bioenergy supply chains. Their model optimized transportation between consumers and facilities while improving total supply chain profits. Sarkar et al. (2024) modeled a bioenergy supply chain for including optimum energy utilization and uncertain lead time using two numerical examples to show the model's effectiveness.

2.2. Circular supply chains

When it comes to sustainable development goals, the circular economy concept offers a fresh perspective, which challenges the current linear economic model (Acerbi & Taisch, 2020). The circular economy has received much attention within production economics and has recently extended to practical business applications (Acerbi & Taisch, 2020). The circular economy principles expand the boundaries of environmental sustainability by organizing the transformation of products to foster viable interactions between ecological systems and economic growth. Nasir et al. (2017) focused on a construction industry case study to show how integrating circular economy principles into sustainable supply chain management can significantly reduce carbon emissions compared to traditional systems. Elia et al. (2017) proposed a framework for the monitoring step of a circular economy. They introduced a four-level framework designed to improve the assessment step, detailing the monitoring processes, the required actions, the necessary criteria to fulfill, and the practical levels of a circular economy strategy. Sassanelli et al. (2019) proposed a framework to evaluate the circularity level of firms. For the Italian textile industry, Bressanelli et al. (2022) considered the factors impacting the circular economy in supply chain management, such as local and regional actors.

Wang et al. (2022) explore product design as a critical entry point for integrating circular principles within supply chain functions. According to 15 interviews, their research identifies four obstacles to circular product design: inadequate infrastructure, financial constraints, global market, and governmental inaction challenges. Key stakeholders capable of addressing these barriers include consumers, industry leaders, and government bodies. Wang et al. (2022) propose strategies such as sustainable waste management, resource circularity, and supply chain collaboration. They develop a practical roadmap for circular product design and contribute to stakeholder theory by examining its role in transitioning supply chains toward a circular economy. Using a case study, Bimpizas-Pinis et al. (2022) investigated the role of supply chain integration in circular supply chains. Their findings showed that companies focused on their forward supply chain to integrate their activities. Moreover, they showed that reverse integration requires forward integration. In circular economy data management, Acerbi et al. (2022) presented a conceptual model, supported by expert interviews, to organize required data to improve decision-making processes in manufacturing firms. Li et al. (2023) provided empirical data to consider circular supply chain management in which government subsidies could positively impact eco-innovation to improve the circular economy. Through a Delphi study, Lima and Seuring (2023) investigated the role of risk in circular supply chains in which coping and reducing strategies were suggested. Bayrak et al. (2024) employed a circular economy for closed-loop supply chains, including durable goods producers, in sales planning problems. Their findings showed that their proposed sales strategy significantly improved total profit while slowing the new-generation diffusion demand.

2.3. Machine learning in circular supply chain

Studies have focused on integrating artificial intelligence and circular supply chain management into renewable energy models (Sassanelli et al., 2023). Alavi et al. (2021) presented a decision support system for sustainably selecting suppliers in circular supply chains. A fuzzy best-worst method evaluated suppliers based on economic, social, and circular criteria. They employed machine learning to evaluate supplier selection criteria. Kabir et al. (2023) employed machine learning algorithms to estimate green hydrogen production in water industries for a circular economy. Using circular economy models, product platforming creates product families using a shared base, maximizing resource use and adapting features to meet customer demand. Akhtar et al. (2024) provided empirical data to explain the moderating role of machine learning in the circular economy. Remanufacturing is necessary for sustainable development and the circular economy, yet sales often fall short of targets due to inadequate marketing strategies despite various practitioner-implemented strategies. Govindan (2024) suggested that machine learning can improve quality and reliability in marketing strategies. Hooda et al. (2024) employed a hybrid machine-learning algorithm to optimize the catalytic pyrolysis of face masks. In circular economy management, Liu et al. (2024) utilized machine learning algorithms to identify patterns and trends in supply chains.

3. Methodology

This paper proposes a multi-objective mathematical model to address the research question. Data for this model was gathered from northwest Oregon forests, using sources such as the US department of transportation, the US forest service, and Oregon geospatial enterprise office, using ArcGIS software. We identified optimized routes and paths using Google's API in the R environment. The branch-and-cut technique obtains the best values for decision variables. It is important to note that estimations were used to transform non-linear relationships into linear ones. This paper uses a case study to show the applicability of the proposed model, along with a sensitivity analysis of 32 scenarios. Next, this paper presents a circular bioenergy supply chain model. Finally, a hybrid machine learning algorithm is presented for optimizing large-scale problems.

3.1. Variables

Variables and notations used in the proposed mathematical model are as follows.

Indices and sets:

a	Residential area, $a \in A$,
i	Harvesting site, $i \in I$,
j	Mobile refinery, $j \in J$,
k	Collection site, $k \in K$,
l	Fixed refinery, $l \in L$,
r	Vehicle type, $r \in R$,
u	Recycling center, $u \in U$,
w	Warehouse site, $w \in W$,

Parameters:

b	Employee working hours per day,
B_s	Storage capacity of location $s \in \{J, K, L, U, W\}$,
C_r	Transportation cost for vehicle r, $r \in \{I, J, K, L, W\}$,
c_s	Total cost of establishing location $s \in \{J, K, L, U, W\}$,
$D_{ss'}$	Distance between location s and location s', $s \neq s'$, $s \in \{A, I, J, K, L, U, W\}$,
e_s	Number of fixed employees at location $s \in \{J, L, U\}$,
F	Minimum woody biomass utilization,
g_s	Production capacity of $s \in \{J, L, U\}$,
H_s	Labor hours needed to produce one ton of biomass at location $s \in \{J, U, L\}$,
M	Big M value,
n_a	Number of available employees at the residential area a,
o_s	Operating cost at location $s \in \{K, J, L, U, W\}$,
p	Price of raw material,
$Q_{rss'}$	Vehicle capacity r to transfer products from location s to s', $s \neq s'$, $s \in \{I, J, K, L, U, W\}$,
S	Percentage yield,
α	Emission factor (kg CO_2e) per mile traveled by each employee,
β	Emission factor (kg of CO_2e) for the production of one ton of biofuel,
γ_r	Emission factor for vehicle type r (kg CO_2e per mile),
θ	Emission factor (kg of CO_2e) for recycling one ton of bio-oil,
λ	Return percentage,
μ	Recycling percentage.

Decision Variables:

$N_{rss'}$	Number of trips from location s to location s', $s \neq s'$, with vehicle r, $s \in \{I, J, K, L, U, W\}$,
P_{as}	People in area a and employed at $s \in \{J, L, U\}$.
T_{uw}	Quantity of the recycled oil transported from u to w,
T_{wu}	Quantity of the returned bio-oil transported from w to u,
X_{ij}	Quantity of biomass that i sends to j,
X_{ik}	Quantity of biomass that i sends to k,
X_{kl}	Quantity of biomass that k sends to l,
Y_{jw}	Quantity of biofuel that j sends to w,
Y_{lw}	Quantity of biofuel that l sends to w,
z_s	Equal to one if location s is open; otherwise, equal to zero, $s \in \{K, J, L, U, W\}$,

3.2. The proposed mathematical model

The mathematical model includes three objectives as follows.

The Economic Pillar of Sustainability: The economic objective consists of the cost of raw materials, the expenses associated with transportation, and the costs related to the location of facilities.

$$\textit{Economic Objective} = RMC + TrC + FLC \tag{1}$$

Total raw material cost (RMC) includes multiplication of the unit raw material price (p) by the total mass of biomass, which is,

$$RMC = p\left(\sum_i\sum_j X_{ij} + \sum_i\sum_k X_{ik}\right) \tag{2}$$

Transportation of biomass and biofuel occurs among five distinct locations, including collection points, harvesting sites, fixed refineries, mobile refineries, and warehouses. This movement is facilitated using various vehicles, specifically large and small semitrailers, and large and small tank trucks. The expense associated with this transportation (TrC) is,

$$TrC = TrC\ of\ biomass + TrC\ of\ biofuel \tag{3}$$

where,

$$TrC\ of\ biomass = \sum_i\sum_j\sum_r C_r D_{ij} N_{rij} + \sum_i\sum_k\sum_r C_r D_{ik} N_{rik} + \sum_k\sum_l\sum_r C_r D_{kl} N_{rkl} \tag{3a}$$

$$TrC\ of\ biofuel = \sum_j\sum_w\sum_r C_r D_{jw} N_{rjw} + \sum_l\sum_w\sum_r C_r D_{lw} N_{rlw} \tag{3b}$$

in which cost is computed by adding up the product of three factors: D_{ij}, representing the optimized distance among locations; C_r, the operating fee of a semitrailer or small tractor-trailer; and N_{rij}, which is the trip number. The trip number is determined by dividing the biomass or biofuel by vehicle capacity.

The facility location cost (FLC) includes various expenses, such as the costs for setting up facilities and the fixed costs for operating and maintaining them, which is,

$$Facility\ Location\ Cost = FLC_b + FLC_a \tag{4}$$

where FLC_a denotes the fixed operational costs as,

$$FLC_a = \sum_k c_k z_k + \sum_l c_l z_l + \sum_j c_j z_j + \sum_w c_w z_w \tag{4a}$$

and FLC_b considers the variable operating costs as,

$$FLC_b = \sum_k\left(\sum_l X_{kl}\right)o_k + \sum_j\left(\sum_w Y_{jw}\right)o_j + \sum_l\left(\sum_w Y_{lw}\right)o_l + \sum_w\left(\sum_j Y_{jw} + \sum_l Y_{lw}\right)o_w \tag{4b}$$

The Environmental Pillar of Sustainability: The environmental objective consists of transportation activities, employee commuting and conversion processes, taking into account the emission factors relevant to each activity, which is,

$$Environmental\ Objective = Transportation\ CO_2 + Conversion\ processes\ CO_2 + Commuting\ CO_2 \tag{5}$$

The total carbon footprint of commuting calculates the distance among residents and their place of work as follows.

$$Commuting\ CO_2 = \alpha\left(\sum_a\sum_j D_{aj}P_{aj} + \sum_a\sum_l D_{al}P_{al}\right) \tag{5a}$$

The total conversion processes carbon is the summation of the products of the quantity of biofuel produced and the specific carbon emission factor for biofuel production (measured in kg CO2e/ton), which is calculated as,

$$Conversion\ processes\ CO_2 = \beta\left(\sum_l\sum_w Y_{lw} + \sum_j\sum_w Y_{jw}\right) \tag{5b}$$

The carbon footprint of transportation is calculated by adding together the products of vehicle trips, distances, and carbon emission factors associated with each vehicle type, which is,

$$Transportation\ CO_2 = \sum_r\sum_i\sum_j D_{ij}N_{rij}\gamma_r + \sum_r\sum_i\sum_k D_{ik}N_{rik}\gamma_r + \sum_r\sum_k\sum_l D_{kl}N_{rkl}\gamma_r + \sum_r\sum_j\sum_w D_{jw}N_{rjw}\gamma_r + \sum_r\sum_l\sum_w D_{lw}N_{rlw}\gamma_r \tag{5c}$$

The Social Pillar of Sustainability: This research utilizes two metrics to evaluate societal impact: job creation and regional workforce (Zarandi et al., 2024). The local workforce is boosted when employees live near their workplaces, thereby reducing total travel distances (Boukherroub et al., 2015). As the environmental objective minimizes commuting carbon, which reduces travel distance, maximizing local employment aligns with the goal of lowering carbon emissions. Therefore, the social objective includes job opportunities as follows.

$$Social\ Objective = \sum_a\sum_j P_{aj} + \sum_a\sum_l P_{al} + \sum_j e_j z_j + \sum_l e_l z_l \tag{6}$$

where the first two terms represent variable personnel working in sites and the last two terms indicate fixed personnel.

Therefore, the three objectives to be optimized are:

Minimize *Economic Objective* shown in Eq. (1).
Minimize *Environmental Objective* shown in Eq. (5)
Maximize *Social Objective* shown in Eq. (6).

Subject to:

$$N_{rij} = \left\lceil \frac{X_{ij}}{Q_{rij}} \right\rceil \forall_i \in I, \forall_j \in J, \forall_r \in R \quad \text{(Vehicle trips)} \tag{7}$$

$$N_{rik} = \left\lceil \frac{X_{ik}}{Q_{rik}} \right\rceil \forall_i \in I, \forall_k \in K, \forall_r \in R \quad \text{(Vehicle trips)} \tag{8}$$

$$N_{rkl} = \left\lceil \frac{X_{kl}}{Q_{rkl}} \right\rceil \forall_k \in K, \forall_l \in L, \forall_r \in R \quad \text{(Vehicle trips)} \tag{9}$$

$$N_{rjw} = \left\lceil \frac{Y_{jw}}{Q_{rjw}} \right\rceil \forall_j \in J, \forall_w \in W, \forall_r \in R \quad \text{(Vehicle trips)} \tag{10}$$

$$N_{rlw} = \left\lceil \frac{Y_{lw}}{Q_{rlw}} \right\rceil \forall_l \in L, \forall_w \in W, \forall_r \in R \quad \text{(Vehicle trips)} \tag{11}$$

$$\sum_i X_{ik} = \sum_l X_{kl} \forall_k \in K, \quad \text{(Inputs and outputs)} \tag{12}$$

$$\sum_j Y_{jw} + \sum_l Y_{lw} = Y_w \forall_w \in W, \quad \text{(Inputs and outputs)} \tag{13}$$

$$\sum_i X_{ik} \le B_k z_k \forall_k \in K, \quad \text{(Status and storage capacity)} \tag{14}$$

$$\sum_i X_{ij} \le B_j z_j \forall_j \in J, \quad \text{(Status and storage capacity)} \tag{15}$$

$$\sum_k X_{kl} \le B_l z_l \forall_l \in L, \quad \text{(Status and storage capacity)} \tag{16}$$

$$\sum_j Y_{jw} + \sum_l Y_{lw} \le B_w z_w \forall_w \in W, \quad \text{(Status and storage capacity)} \tag{17}$$

$$\sum_a P_{aj} \le M z_j \forall_j \in J, \quad \text{(Functioning status)} \tag{18}$$

$$\sum_a P_{al} \le M z_l \forall_l \in L, \quad \text{(Functioning status)} \tag{19}$$

$$\sum_a P_{aj} = \left\lceil \frac{(H_j \times \sum_w Y_{jw})}{b} \right\rceil \forall_j \in J, \quad \text{(Number of employees)} \tag{20}$$

$$\sum_a P_{al} = \left\lceil \frac{(H_l \times \sum_w Y_{lw})}{b} \right\rceil \forall_l \in L, \quad \text{(Number of employees)} \tag{21}$$

$$\sum_j P_{aj} + \sum_l P_{al} \le n_a \forall_a \in A, \quad \text{(Employees available)} \tag{22}$$

$$Y_j \le g_j \ \forall_j \in J, \quad \text{(Production capacity for biofuel)} \tag{23}$$

$$Y_l \le g_l \forall_l \in L, \quad \text{(Production capacity for biofuel)} \tag{24}$$

$$S \times \sum_i X_{ij} = \sum_w Y_{jw} \forall_j \in J, \quad \text{(Biomass converted to biofuel)} \tag{25}$$

$$S \times \sum_k X_{kl} = \sum_w Y_{lw} \forall_l \in L, \quad \text{(Biomass converted to biofuel)} \tag{26}$$

$$\sum_i \left(\sum_j X_{ij} + \sum_k X_{ik} \right) \le F \quad \text{(Available woody biomass)} \tag{27}$$

$$X_{ij}, X_{ik}, X_{kl}, Y_{jw}, Y_{lw} \ge 0 \quad \text{(Continuous decision variables)} \tag{28}$$

$$N_{rij}, N_{rik}, N_{rkl}, N_{rjw}, N_{rlw} \ge 0, int \quad \text{(Integer decision variables)} \tag{29}$$

$$z_j, z_k, z_l, z_w = \{0, 1\} \quad \text{(Binary decision variables)} \tag{30}$$

$$P_{aj}, P_{al} \ge 0, int \quad \text{(Integer decision variables)} \tag{31}$$

Eqs. (7)–(11) shows the number of vehicle trips. An estimation method is employed to simplify non-linear relationships into linear ones. Eq. (12) balances input and output at sites. Similarly, Eq. (13) confirms that the total mass of biofuel processed by refineries matches the mass of biofuel dispatched to warehouses. Eqs. (14)–(17) shows the working status and the storage capacities. Eqs. (18)–(19) similarly state that employees commute solely to functioning refineries. Eqs. (20)–(21) calculate the workforce at refineries. The recruitment from a specific region cannot exceed the total available workforce in that region, as defined in Eq. (22). Eqs. (23)–(24) refer to the production capacities. The conversion of biomass to biofuel in these refineries includes some losses, accounted for by a yield percentage parameter, shown in Eqs. (25)–(26). Eq. (27) shows the supply-oriented model, which can use all available biomass. Eqs. (28)–(31) show the variables domain.

The impact of the mobile refinery on the objectives compared with the fixed refinery is captured by binary variables. Mobile refineries have several advantages over fixed refineries. First, mobile refineries offer flexibility in location and can dynamically respond to changes in demand, potentially increasing profits. The binary variables represent this flexibility in the model, indicating whether a mobile refinery site is operational. Second, mobile refineries improve resource utilization by quickly relocating to available areas, allowing them to process biomass closer to its source. This flexibility is particularly advantageous as resource availability can vary throughout the year. Last but not least, the inclusion of mobile refineries allows the model to optimize routes dynamically, potentially leading to lower costs.

3.3. *The case study: A bioenergy supply chain*

This study focuses on a case study in northwest Oregon's forests, addressing three key areas: environmental, social, and economic issues. Environmentally, 2021 saw over five million acres of US forests, including half a million in Oregon, being consumed by fires. Socially, Oregon's unemployment rate is 4.2 (the US minimum unemployment rate: 2), influencing its public education and personal safety rankings in 2024. Economically, Oregon ranks 42 in the US in GDP, with significant expenses due to forest fires in 2024. Therefore, key focus includes total cost, carbon footprint, and job creation.

At the harvesting sites, available biomass is transported either directly to mobile refineries or to collection sites using small tractor-trailers. These collection sites function as biomass hubs, enabling the transfer of substantial biomass quantities to fixed facilities or refineries via large tractor-trailers. Both fixed and mobile refineries are involved in biofuel production, with their output dependent on the yield percentage and refinery capacity. Transport of biofuel from mobile refineries to warehouses is conducted using small tanker trucks, while large tanker trucks are employed for the same purpose for fixed refineries.

Biomass, forest residues, is valued at $25 per ton, and the product, biofuel, is estimated to be priced between $0.78 and $1.76 per gallon. Biofuel's characteristics, such as density and energy content, are also considered. Four counties in northwest Oregon are identified as significant biomass sources using data from the U.S. Forest Service. The study selects multiple sites for harvesting, collection, refineries, and warehouses in northwest Oregon. Warehouse selection is based on storage costs and proximity to refineries, considering third-party warehousing services. Employee availability calculations utilize the 2024 US average unemployment rate and population. We used the person-hour factor for biofuel production. The environmental impact, including biomass collection and pyrolysis, is quantified in terms of carbon. Emission factors for vehicles are also considered. A just-in-time production and biomass flow approach is adopted to minimize inventory costs.

4. The case study result

The case study was implemented in CPLEX 12 using Windows 10 (Core i5, 3.40 GHz, and 16 GB RAM). The model utilized the weighted goal programming technique to obtain Pareto solutions to illustrate the trade-offs between societal, economic, and environmental goals. When it comes to multi-objective optimization models, the weighted goal programming technique is a common method to transform the models to a single objective model (Boukherroub et al., 2015). For more details and examples, interested readers are referred to see Hashemi-Amiri et al. (2023), Wang et al. (2023), and Romero (2014). This method includes three main steps. In the first step 1, each objective function is assigned a target value (called goal), and the approach minimizes the deviations from these targets by using a weighted sum of the deviations. For each objective function's target value, we use the best value obtained by optimizing each function solely without considering other objectives. For example, we optimize the model for the economic objective by ignoring other objectives. In the second step, we calculate the relative deviations which are added to the mathematical model. Normalization of the three objectives was a prerequisite to using weighted goal programming due to their differing scales. The third step includes transformation and optimization. In the final step, we use a vector of weights, which is summed to one, to transform the model into a single objective problem. Adjusting these weights allows decision-makers to explore various Pareto optimal solutions.

The CPLEX solver processed the model, which consisted of 1,690 variables, 1,045 constraints, and over 10,577 iterations. The optimized outcomes for each objective, considered individually, are shown in Table 1. For instance, the second column shows the optimal economic solution, predicting a biofuel cost of $1.34/gal within the market range. This scenario would require ninety employees, leading to a total carbon emission of 5,369 kg CO2e, broken down into commuting, conversion processes, and logistics emissions. A radar graph in Fig. 1 visualizes these normalized optimal solutions, indicating that each is non-dominated and excels in at least one indicator. This graph also illustrates the trade-offs between objectives; for example, focusing on the social aspect might reduce economic and environmental performance. Table 2 shows a comparative analysis with a traditional model. This

Table 1
Optimal solutions.

Weighting: Objective:	(1,0,0) Min. Total Cost	(0,1,0) Min. Carbon Footprint	(0,0,1) Max. Jobs Created
Economic	$819,756	$5,586,835	$7,476,347
Environmental	5,369 kg CO2e	3,507 kg CO2e	46,699 kg CO2e
Societal	90	126	347
Cost of biofuel	$1.34/gal	$9.17/gal	$3.11/gal

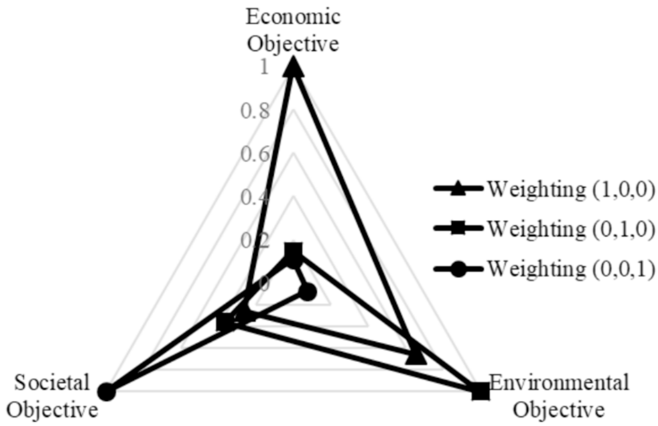

Fig. 1. Radar graph for objectives.

Table 2
Case study results.

Variables	Proposed model	Traditional model
Cost	\$1.34/gal	\$4.48/gal
Commuting carbon	175 kg CO2e	271 kg CO2e
Conversion carbon	1609 kg CO2e	1609 kg CO2e
Transportation carbon	3585 kg CO2e	2009 kg CO2e
The number of jobs created	90 people	90 people

comparison reveals that incorporating mobile refineries reduces biofuel costs significantly, from \$4.48/gal to \$1.34/gal, offering a clear advantage over traditional methods. The calculation of the predicted biofuel cost considers the total cost and the total volume produced. Mobile refineries also reduce commuting-related emissions, though emissions from conversion processes remain unchanged. Despite having a higher transportation carbon footprint due to larger tanker trucks and fewer trips, the mixed biofuel supply chain, incorporating both fixed and mobile refineries, demonstrates an overall advantage.

4.1. Sensitivity analysis

This paper conducted a sensitivity analysis of 32 different scenarios to evaluate the effects of inputs on outcomes. These parameters are the capital cost of mobile refineries, operating costs of refineries, the total quantity of available woody biomass, the storage capacity of mobile refineries, and the percentage yield of the process. Each parameter is evaluated under low- and high-value scenarios, which are then compared to a baseline scenario regarding objective functions as follows.

Six scenarios examine the effects of varying mobile refinery capital costs, with increases and decreases of 10%, 20%, and 30%. Higher capital costs lead to increases in the total and facility location costs, as well as the predicted cost of biofuel. For instance, a 30% rise in capital cost raises the facility location cost by 21% and the biofuel cost by 17%. However, the carbon footprint and job creation remain unchanged. Moreover, six scenarios assess the influence of operating cost fluctuations on similar variables. Increases in operating costs marginally affect the objectives. A 30% hike in operating costs leads to a 4% rise in the predicted biofuel cost, with no significant change in the carbon footprint or job creation. Besides, variations in percentage yield, ranging from −30% to +30%, impact all three objectives. Improved yields increase logistics activities, raising job creation and transportation-related carbon emissions. When we improve yield by 30%, total costs increases by 4% but reduces the unit cost of biofuel by 20%, highlighting benefits in economic and societal aspects. Furthermore, changes in storage capacity significantly affect the biofuel supply chain. A 10% reduction in storage capacity increases the number of active mobile refineries, whereas a 40% increase decreases the number of refineries needed. Enhanced storage capacity leads to a 19% decrease in biofuel cost but reduces job creation by 10% and increases the carbon footprint by 9%. In addition, examining the impact of available woody biomass, the study finds that increases in biomass availability linearly raise all objectives. A 40% increase in biomass availability lowers the unit cost of biofuel by 6%, boosts job creation by 38.8%, and increases the carbon footprint by 43%.

Overall, results indicate that optimizing mobile refinery capital and operating costs can significantly reduce biofuel costs. Improving the percentage yield enhances economic and societal outcomes, while adjustments in storage capacity and available biomass have varying impacts on all three objectives. Notably, while increasing biomass availability is beneficial for economic and societal aspects, it adversely affects the environmental objective due to increased carbon emissions. The net environmental impact of biofuel production, considering aspects like fossil fuel savings, remains a topic for future research.

5. Circular bioenergy supply chain

This section develops the case study to include the circular economy paradigm. The circular economy paradigm has received much attention as a potential alternative for the linear economic models (Acerbi & Taisch, 2020). The linear economic models follow a take-make-dispose approach, which ignores waste management (Farooque et al., 2019). The linear approach is considered an unsustainable solution, which generates waste and pollutes environment while consumes significant amount of natural resources (Lahane et al., 2020). The circular economy is emerging as an essential stimulus for sustainability in scholarly literature and practical applications (Castro et al., 2022). Generally, the circular supply chain includes six main principles: reuse, reduce, recycle, redesign, remanufacture, and repair of used products, by-products, and services (Farooque et al., 2019; Lahane et al., 2020; Rosa et al., 2020).

When vendors conduct quality control upon receiving products, two possibilities exist: return or buy. We added this condition to the model, where returned products are processed to produce new items. One of the most effective strategies to manage waste is to view it as raw material for a new product. A retail example is creating yogurt or cheese from milk nearing its expiration date. In a similar vein, lower-quality oil can be repurposed for lubrication or other uses. We consider a set of recycling centers ($u \in U$) to produce or refine a new product from received low-quality oil, T_{wu} with fuzzy numbers for inputs. There is a return percentage (λ), which creates $T_{wu} \geq 0$, the returned oil from warehouse (w) to recycling centers (u), which are open ($z_u = 1$). Therefore, the returned oil will be processed as the second product (T_{uw}) in recycling centers to send it to warehouses using N_{ruw} and N_{rwu} vehicle trips. Moreover, we consider $P_{au} \geq 0$, the number of workers living in the area a and employed at u. In the proposed circular supply chain, the transportation cost of return and resend are added to the transportation of the finished products in Eq. (3b) as,

$$\sum_j \sum_r \sum_w C_r D_{jw} N_{rjw} + \sum_l \sum_r \sum_w C_r D_{lw} N_{rlw} + \sum_w \sum_u \sum_r C_r D_{wu} N_{rwu} + \sum_u \sum_w \sum_r C_r D_{uw} N_{ruw} \tag{32}$$

Eq. (4a) is updated with a fixed cost of operations in recycling centers as,

$$\sum_k c_k z_k + \sum_l c_l z_l + \sum_j c_j z_j + \sum_w c_w z_w + \sum_u c_u z_u \tag{33}$$

Moreover, Eq. (4b) is updated with a variable operating cost of recycling centers as,

$$\sum_k\left(\sum_l X_{kl}\right)o_k+\sum_j\left(\sum_w Y_{jw}\right)o_j+\sum_l\left(\sum_w Y_{lw}\right)o_l+\sum_w\left(\sum_j Y_{jw}+\sum_l Y_{lw}\right)o_w+\sum_w\left(\sum_u T_{wu}\right)o_u \tag{34}$$

The carbon footprint of commuting, conversion processes, and transportation are added to Eq. (5a), Eq. (5b), and Eq. (5c), respectively, as,

$$\alpha\left(\sum_a\sum_j D_{aj}\times P_{aj}+\sum_a\sum_l D_{al}\times P_{al}+\sum_a\sum_u D_{au}\times P_{au}\right) \tag{35}$$

$$\beta\left(\sum_l\sum_j\sum_w(Y_{lw}+Y_{jw})\right)+\theta\left(\sum_w\sum_u T_{wu}\right) \tag{36}$$

$$\sum_r\sum_i\sum_j D_{ij}N_{rij}\gamma_r+\sum_r\sum_i\sum_k D_{ik}N_{rik}\gamma_r+\sum_r\sum_k\sum_l D_{kl}N_{rkl}\gamma_r+\sum_r\sum_j\sum_w D_{jw}N_{rjw}\gamma_r+\sum_r\sum_l\sum_w D_{lw}N_{rlw}\gamma_r+\sum_r\sum_w\sum_u D_{wu}N_{rwu}\gamma_r+\sum_r\sum_u\sum_w D_{uw}N_{ruw}\gamma_r \tag{37}$$

Finally, the variable and fixed workforce who work in each recycling center are added to Eq. (6),

$$\sum_a\sum_j P_{aj}+\sum_a\sum_l P_{al}+\sum_a\sum_u P_{au}+\sum_j e_j z_j+\sum_l e_l z_l+\sum_u e_u z_u \tag{38}$$

We update Eq. (17) to include the recycled oil as,

$$\sum_j Y_{jw}+\sum_l Y_{lw}+\sum_u T_{uw}\le B_w z_w,\forall_w\in W \tag{39}$$

Moreover, the number of available employees is updated as,

$$\sum_j P_{aj}+\sum_l P_{al}+\sum_u P_{au}\le n_a,\forall_a\in A \tag{40}$$

Last but not least, the proposed circular bioenergy supply chain model also has the following constraints.

$$N_{rwu}=\left\lceil\frac{T_{wu}}{Q_{rwu}}\right\rceil\forall_u\in U,\forall_w\in W,\forall_r\in R \tag{41}$$

$$N_{ruw}=\left\lceil\frac{T_{uw}}{Q_{ruw}}\right\rceil\forall_u\in U,\forall_w\in W,\forall_r\in R \tag{42}$$

$$\lambda\left(\sum_j Y_{jw}+\sum_l Y_{lw}+\sum_u T_{uw}\right)=\sum_u T_{wu},\forall_w\in W \tag{43}$$

$$\sum_w T_{wu}\le B_u z_u,\forall_u\in U, \tag{44}$$

$$\sum_w T_{uw}\le g_u,\forall_u\in u, \tag{45}$$

$$\mu\times\sum_w T_{wu}=\sum_w T_{uw},\forall_u\in U \tag{46}$$

$$\sum_a P_{au}\le Mz_u,\forall_u\in U \tag{47}$$

$$\sum_a P_{au}=\left\lceil\frac{(H_u\times\sum_w T_{wu})}{b}\right\rceil\forall_u\in U \tag{48}$$

5.1. A hybrid machine-learning algorithm

Machine learning algorithms can significantly improve metaheuristics in optimization processes. Karimi-Mamaghan et al. (2022) provided a review of machine learning algorithms used in metaheuristics. This section introduces a hybrid machine learning algorithm integrating the K-means clustering algorithm with the genetic algorithm to address large-scale supply chain models.

Interested readers can review Jaggia et al. (2023, Chapter 11) and Katoch et al. (2021) for more details and numerical examples about K-means clustering and genetic algorithms, respectively. Genetic algorithms work as population-based metaheuristics, finding the best solution in a pool of possible solutions after several iterative processes. Randomly chosen candidate solutions create a new generation of solutions through iterative steps (Gabellini et al., 2024; Han et al., 2023). The population-based characteristic of genetic algorithms can cause premature convergence and scalability issues. We employ the K-means algorithm, an unsupervised machine learning algorithm, to mitigate these issues. The K-means algorithm groups data points into clusters based on their similarity.

The hybrid algorithm works as follows. First, an initial population of chromosomes (candidate solutions) is created along with the corresponding fitness function. Second, the K-means algorithm provides five clusters of chromosomes based on similarities in their objective functions. The K-means algorithm iteratively assigns candidate solutions to the nearest cluster center and recalculates cluster centers until convergence (X. Li et al., 2023). Third, the genetic algorithm's operators create a new generation of solutions by randomly selecting two parents from the clusters. This approach makes the genetic algorithm quicker and more accurate, addressing premature convergence and scalability issues. This hybrid algorithm iterates the last step until the stopping criteria are met, which is set at 200 generations. The parameters are tuned: population size:50, cluster number:5, crossover rate:0.7, mutation rate:0.2, and iterations:200.

The proposed algorithm is used to optimize the presented circular bioenergy supply chain, and the results show that there are 73,300 returned gallons for three percent returned oil, which adds $513,100 to the total cost of $868,142. Using two recycling centers ($u = 2$), the recycled oil includes 74,760 gallons, consisting of 62,300 gallons of reprocessed oil and 20% of added materials. The findings support the circular supply chain versus linear supply chain in which costs (1,366,978 versus 1,381,242), carbon footprints (2,699 versus 4,242), and number of job opportunities (113 versus 100) are better managed.

Findings in Table 3 showed that the hybrid machine learning algorithm could quickly provide optimal or near-optimal solutions for large-scale problems in biomass to biofuel supply chains by addressing costs, carbon emissions, and job opportunities.

6. Discussion and conclusions

This study's primary goal was to create a circular bioenergy supply chain for a biofuel logistics-production problem incorporating mobile or movable facilities, with a particular emphasis on sustainability aspects. Unlike most existing studies that focus on supply chains with stationary refineries, this research emphasizes the use of mobile refineries, a less-explored area. The novel contribution of this work lies in investigating the sustainability impacts and the circular economy approach in bioenergy supply chains.

This research developed a model for a mobile facility supply chain, producing biofuel from woody forest biomass, centered around three key sustainability pillars: economic, environmental, and social aspects. These were translated into three distinct objectives within the model: minimizing total costs, reducing the overall carbon footprint, and maximizing job creation. The model's parameters and objectives were estimated using empirical data. We solved the proposed model and determine a range of Pareto solutions using the weighted goal programming technique, offering a comprehensive view of the trade-offs between these three critical sustainability objectives. Moreover, this paper extended the proposed model to include triangular fuzzy inputs for large-scale problems. To optimize large-scale problems, we proposed a hybrid machine learning algorithm, which included a genetic algorithm and a K-mean algorithm. Findings showed that a hybrid machine learning algorithm with metaheuristic can provide a viable solution for

Table 3
Numerical examples.

	Example (a, i, j, k, l, r, w)	The proposed algorithm				The exact method*			
		Economic objective (10e6)	Environmental objective (10e5)	Social objective	Time (second)	Economic objective (10e6)	Environmental objective (10e5)	Social objective	Time (second)
Small size problems	(2, 20, 2, 2, 2, 2, 2)	9.30	6.41	57	0.97	8.45	5.79	66	0.11
	(3, 25, 3, 3, 3, 3, 3)	10.53	6.62	83	1.09	9.36	5.89	99	0.28
	(4, 30, 4, 4, 4, 4, 4)	12.10	7.72	92	1.75	10.78	6.93	132	4.3
	(5, 35, 5, 5, 5, 5, 5)	13.33	8.37	113	2.96	11.83	7.31	165	277
	(6, 40, 6, 6, 6, 6, 6)	14.33	9.32	158	6.38	12.88	8.40	198	4.8
Medium size problems	(7, 50, 7, 7, 7, 7, 7)	16.45	10.71	189	7.91	14.55	9.33	231	106.2
	(9, 60, 9, 9, 9, 9, 9)	18.58	12.19	246	11.07	16.26	10.93	288	976.2
	(11, 70, 11, 11, 11, 11, 11)	21.41	13.70	275	11.84	18.90	11.99	303	2403
	(13, 80, 13, 13, 13, 13, 13)	24.30	15.07	299	12.17	21.51	13.42	328	8618
	(15, 90, 15, 15, 15, 15, 15)	26.43	16.60	313	12.35	23.58	14.89	351	19,632
Large size problems	(20, 100, 20, 20, 20, 20, 20)	41.90	57.89	374	15.99	> 6 h	> 6 h	> 6 h	> 6 h
	(25, 150, 25, 25, 25, 25, 25)	117.98	140.47	392	19.28	> 6 h	> 6 h	> 6 h	> 6 h
	(30, 200, 30, 30, 30, 30, 30)	270.13	290.13	407	21.58	> 6 h	> 6 h	> 6 h	> 6 h
	(35, 250, 35, 35, 35, 35, 35)	346.21	367.48	431	23.43	> 6 h	> 6 h	> 6 h	> 6 h
	(40, 300, 40, 40, 40, 40, 40)	498.36	419.04	454	25.21	> 6 h	> 6 h	> 6 h	> 6 h

* The GAMS code is available on www.github.com/naricode/CAIE2024.

large-scale problems.

The model's prediction for biofuel costs aligned with the cost range identified in market data and research literature. A comparative analysis between a supply chain with mobile facilities and a traditional biofuel supply chain reliant solely on fixed refineries revealed that mobile refineries could substantially lower biofuel costs from $4.48 per gallon to $1.34 per gallon. Thus, integrating mobile refineries into biofuel supply chains could offer a significant economic edge. Furthermore, a sensitivity analysis exploring the impact of five critical parameters across 32 scenarios revealed that variations in the capacity of mobile refineries and the percentage yield had more pronounced effects on the key objectives than other parameters. An increase in percentage yield by 10–30% was observed to decrease both the anticipated cost of biofuel and job creation by 7–20% and 8–21%, respectively. Similarly, expanding the capacity of mobile refineries by 10–40% was shown to lead to a significant reduction in biofuel costs, potentially dropping as much as 19% from $1.42 per gallon to $1.16 per gallon. Correspondingly, Hoefnagels et al. (2013) emphasized the need for technological development to enable sustainable energy systems. In large-scale production of bioenergy from a variety of sources, they showed that there is a need for high rates of technological change to reduce greenhouse gas emissions. Mobile refineries offer technological innovation to reduce the total costs and environmental impacts of biofuel production.

6.1. Managerial and practical implications

Several managerial and practical implications exist for utilizing the model employed in this research. These implications not only benefit stakeholders involved in the biofuel industry but also provide a roadmap for sustainable growth in renewable energy sectors.

In response to the global extension of wildfire seasons, urgent assistance is required for both private and public sector management of land and forests to mitigate wildfire incidents. The United States has not experienced a significant increase in wildfires over the past thirty years, yet the amount of land affected and carbon emissions have risen substantially (Cortés-Murcia et al., 2022). Wildfires not only destroy property and homes but also have wider social and environmental effects, such as human harm, damage to infrastructure, wildlife habitats, and water quality. Wildfire damage in the US has a significant economic impact of billions of dollars each year (Fann et al., 2018). This increasing severity of wildfires highlights the necessity for societal involvement in devising effective mitigation strategies. Accumulated dried woody biomass in forests is a significant factor that contributes to wildfire risk. A suggested solution for reducing this risk involves sustainable biofuel production.

The proposed model introduced in this paper is designed to help decision-makers in biofuel supply chains that utilize a combination of fixed and mobile facilities, which focuses on enhancing different aspects of sustainability performance. The proposed model shifts the emphasis away from purely monetary considerations, which enables a balanced consideration of environmental, societal, and economic factors. The application of this model demonstrates that, in addition to addressing wildfire risks and energy dependency, societal considerations can yield economically competitive biofuel prices.

Conventional industrial production and consumption mechanisms have been rooted in the linear economic models (take-make-consume-dispose cycle) (Farooque et al., 2019), which is sometimes called the cradle-to-grave methodology of production and consumption. Decision-makers can employ the proposed circular supply chain to reduce waste by creating value. For example, urban populations worldwide produce approximately 1.3 billion tons of solid waste annually, which is anticipated to ascend to 2.2 billion tons by 2025 (Lahane et al., 2020). There is a pressing imperative to transition toward a sustainable production paradigm within supply chains, which is epitomized by the circular economy concept (Lahane et al., 2020).

A key finding of the research is the significant potential for cost savings through the integration of mobile refineries. Traditional logistics networks that rely on fixed refineries face challenges in terms of cost efficiency, especially in areas in which transportation and logistics activities have barriers. The optimization of biofuel production in uncertain supply chains requires a dynamic approach, which is addressed in this paper. Mobile refineries offer flexibility by which transportation costs can be decreased and biomass processing will be closer to the source.

The research highlights the environmental benefits of a bioenergy circular supply chain. Decision-makers can balance economic viability and environmental responsibility with a focus on carbon footprints. Hoefnagels et al. (2010) highlighted the understanding of carbon footprints of biofuel production-logistics systems. This paper explains the environmental benefits of mobile refineries, especially when considering the complete lifecycle of biofuel production, which can help managers make decisions that take the environment into consideration while still focusing on the bottom line of the company.

This paper has significant societal implications. By emphasizing job creation as one of the pillars of sustainability, the research aligns with Elkington's Triple Bottom Line framework (Elkington, 2013), which advocates for a balance between economic, environmental, and social outcomes. In regions with high unemployment rates or areas affected by deforestation or forest fires, biofuel production can stimulate local economies, creating jobs and fostering economic growth.

Mobile refineries represent a technological and practical business innovation in the biofuel industry. As Mobini et al. (2011) discussed, forest biomass supply logistics networks can benefit from technological advancements and innovative approaches. The emphasis on mobile refineries indicates a shift towards more adaptive and technologically advanced logistics networks and models. Managers and decision-makers can invest in research and development, focusing on refining the technology behind mobile refineries to improve sustainability.

6.2. Limitations and future research

Our findings are limited to Oregon data. Moreover, a random variable is not considered in this paper, which limits the applicability of the proposed model for the uncertain conditions of parameters such as moisture and quality of raw materials. In this study, societal impacts within the supply chain were evaluated primarily through two indicators: job creation and local employment. Future research should expand the range of societal metrics to assess the sustainability performance of bioenergy supply chains more comprehensively. These metrics should be carefully selected and quantified to effectively measure and manage the contributions of bioenergy supply chains. For instance, one of the sustainable development goals set by the United Nations includes the "proportion of people under 25 without employment," aiming to foster "sustained, inclusive and sustainable economic growth, and decent work for all." Such indicators could provide valuable insights into the broader societal impacts of bioenergy supply chains. Future research can investigate the role of technology in circular supply chain management (Chiappetta Jabbour et al., 2020). For example, Blockchain technology can be utilized to ensure the traceability of raw materials from their source through to the final product (Chiappetta Jabbour et al., 2020). Moreover, big data analytics can process vast amounts of data to predict the future condition of supply chain parameters under uncertain conditions.

CRediT authorship contribution statement

Kiarash Sadeghi R. & Moein Qaisari Hasan Abadi: Writing – review & editing, Conceptualization, Methodology. **Karl R. Haapala:** Writing – review & editing, Conceptualization. **Joseph R. Huscroft:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Authors shared the code and data here https://github.com/naricode/CAIE2024.

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