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Closed-loop supply chain planning for bioenergy production from Jatropha and Paulownia biomass: A case study

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Abstract
This paper employs a multi-objective linear integer programming optimization model for bioenergy supply chain planning to optimize total costs and total bioenergy production from Jatropha and Paulownia biomass. The model incorporates various decisions, including the allocation of farms to different biorefineries using two transportation modes (road and rail), determining the flow of raw materials from farms to biorefineries and optimizing the quantities of bioenergy production. In addition to energy considerations, the model also addresses water usage, thereby incorporating the water-energy nexus framework. In order to solve the model, ε-constraint method is applied. The case study focuses on farms in southern and southwestern Iran. The results clearly demonstrate that implementing the closed-loop model significantly reduces overall supply chain network costs.

Keywords: Biomass supply chain; Jatropha and Paulownia; Closed-loop; Bioenergy; Water-energy nexus.

1. Introduction

Although fossil fuels such as oil and gas are not evenly distributed geographically and exist in limited quantities, they still constitute for the majority of global energy consumption today (Shirazaki et al. (2024) [1]). This heavy reliance on fossil fuels has led to significant environmental pollution (Shirazaki et al. (2024) [1]). Iran is among the world's richest countries in the field of oil and gas resources. Currently, about 98% of the country's energy consumption is supplied by fossil fuels (Shirazaki et al. (2024) [1]). As a result, in recent years, governments have been making efforts to increase the share of renewable energy in the country's energy mix (Shirazaki et al. (2024) [1]). Meeting most energy demands through fossil fuels has led to significant environmental and public health challenges (Gital & Bilgen (2024) [2]). In addition, using and combustion fossil fuels release a huge amount of pollution and greenhouse gases (GHG) into the environment (Hosseinitabar et al. (2024) [3]). recent research confirms that air pollution plays a significant role in both the emergence and exacerbation of various diseases (Rasekh et al. (2023) [4]).

Studies indicate that due to population and economic growth in the East, energy consumption in this region will increase by approximately 20–30% by 2040. Liquid fuels account for the highest share of energy demand, particularly in the transportation sector (Bahmani et al. (2024) [5]).

Renewable energy sources such as solar and hydroelectric power can only generate electricity, which faces significant challenges in long-distance transmission and energy conversion to other forms. Consequently, these energy sources are less attractive compared to fossil fuels. In contrast, biomass possesses the distinct advantage of being convertible into multiple forms of energy, making it a more versatile energy alternative (Gitinavard et al. (2025) [6]). Additionally, while wind and solar energy systems require substantial capital investment, biomass-based renewable energy offers significantly lower costs (Nugroho & Zhu (2024) [7]).

Over the past twenty years, biomass resources have been categorized into three distinct groups: first, second, and third-generation feedstocks (Singh et al. (2023) [8]). First-generation biofuels include agricultural crops such as barley and rice, as well as food products like starch and sugar. Second-generation biofuels comprise non-edible materials, including agricultural residues and plants like Jatropha and Paulownia. Finally, third-generation biofuels consist of microalgae (Pishvaee et al. (2021) [9]). Among these, first-generation biomass is the most commercially viable, easily accessible, and poses fewer ecological concerns (Singh et al. (2023) [8]).

Jatropha is considered one of the few plants that exhibit high resistance to varying water and soil conditions, while producing valuable oilseeds for biodiesel and glycerol production (Gilani & Sahebi (2024) [10]). Additionally, Jatropha has multiple environmental and socioeconomic benefits, such as adaptability to degraded soils, erosion control,

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enhanced water retention, drought resistance, minimal irrigation and fertilizer needs, reduced carbon emissions, and support for rural economies (Babazadeh et al. (2019) [11]). The seed kernel of Jatropha contains approximately 30–40% oil, making it one of the highest-yielding oil sources among both edible and non-edible bioenergy crops (Babazadeh et al. (2019) [11]). This oil can be obtained through multiple extraction techniques, including mechanical pressing methods that utilize specialized equipment (Afkhami & Zarrinpoor (2021) [12]). Biofuels such as biodiesel can be blended with conventional diesel fuel (e.g., Petrodiesel) in proportions of up to 20% and used directly in diesel engines without major modifications (Bahmani et al. (2024) [5]). Additionally, biofuels are recognized for being sustainable, non-polluting, biodegradable, and easily transportable, making them a viable alternative to conventional fuels (Singh et al. (2023) [8]).

The biomass-to-bioenergy process must ensure streamlined material, informational, and financial flows for maximum effectiveness (Mahjoub at al. (2020) [13]). A biomass supply chain (BSC) represents an interconnected system linking feedstock producers, conversion facilities, and end-users through a multi-stage operational framework. This complex network encompasses dynamic processes spanning agricultural land utilization, crop cultivation and collection, feedstock preservation, bioenergy conversion, and final product delivery to markets (Gital & Bilgen (2024) [2]). The bioenergy supply chain comprises three key segments: upstream (biomass production/transport), midstream (conversion processing), and downstream (energy storage/distribution) (Mahjoub at al. (2020) [13]). Differences in climate, geography, and resource availability make it impractical to rely on a single biomass type universally. Even where feasible, energy output may be insufficient. Thus, integrating multiple biomass generations enhances supply chain flexibility, allowing optimal feedstock selection based on regional conditions (Mahjoub at al. (2020) [13]). One alternative strategy to ensure reliable biomass feedstock supply involves implementing multi-source procurement approaches. Enhancing the supply security of biomass feedstocks could significantly increase the adoption rate of biomass-based energy (Nugroho & Zhu (2024) [7]).

The rapidly growing population and expanding industrial activities have led to a significant increase in energy demand. Given the heightened focus on energy and water consumption within the framework of sustainable community development and carbon reduction, considering the water-energy nexus has become essential (Rasekh et al. (2023) [4]). In the continuation of this paper, section 2 provides a review of prominent recent research in the field of biomass supply chain planning. In section 3, the studied problem is described and the mathematical model is presented. Section 4 provides the case study, computational results and analysis. Finally, section 5 presents conclusions of the research, along with recommendations for future work.

2. Literature review

Due to the significant and often irreversible environmental impacts of fossil fuels, alternative energy sources have become a global priority and has attracted the attention of industrial and academic research in last decade. Global biofuel production and biomass utilization have experienced significant growth since 2020. In that year, biogas production reached 38 billion m^3 and liquid biofuel production amounted to 146 billion liters (Hosseinitabar et al. (2024) [3]). The annual number of publications on second-generation biomass (e.g., Jatropha) has shown a consistent increasing trend in recent years. This section provides a critical review of prominent studies in this field published.

Ghelichi et al. (2018) [15] presented a multi-period, multi-product and two-stage stochastic environmentally friendly model for designing a green biodiesel supply chain network. Uncertainties in model were applied in both fuel demand projections and the seed yield potential of Jatropha plants. Babazadeh et al. (2019) [11] developed a possibilistic optimization model to design a second-generation biodiesel supply chain network. the model had one objective function minimizing the total cost of the network. they considered waste cooking oil and Jatropha as feedstock, and biodiesel and glycerin as final products. Mahjoub at al. (2020) [13] presented a multi-period and multi-objective model for agricultural residues, livestock manure, microalgae and Jatropha as feedstocks. The performance of their model was evaluated through conducting a real case study. The results showed that the amount of produced bioenergy from microalgae and Jatropha are able to produced more energy. Afkhami & Zarrinpoor (2021) [12] proposed a multi-period, multi-objective and multi-product in a biodiesel supply chain network using second generation biomass. They considered sustainable development and global market demand and solved the problem through an interactive fuzzy optimization approach. Yazdanparast et al. (2022) [14] developed a two-stage stochastic programming model incorporating the potential supply and production disruptions to optimize drop-in biofuel supply chain. Conditional value-at-risk was considered as a risk measurement metric. Singh et al. (2023) [8] developed a multi-objective optimization model to minimize both biodiesel supply chain costs and environmental impacts. Their model incorporated demand elasticity influenced by government subsidies and advertisement expenditures. Furthermore, the authors implemented a social impact assessment method integrated with life cycle thinking to systematically evaluate societal implications. Rasekh et al. (2023) [4] by considering two different generations of biomass (second and third-generation), developed a multi-period optimization model incorporating five objectives: job creation, increased energy production, cost reduction, water consumption minimization, and carbon emission reduction. The results demonstrate that Jatropha yields higher energy output compared to other examined feedstocks.

Bahmani et al. (2024) [5] presented a tri-objective optimization model under robust uncertainty that simultaneously minimizes total cost, non-resiliency, while maximizing positive social impacts. The model incorporated risk considerations, disruption scenarios and transportation constraints. Gital & Bilgen (2024) [2] in their review article, conducted an extensive and meticulous analysis on last researches in the field of biomass supply chain design under uncertainty. Hosseinitabar et al. (2024) [3] employed a two-stage stochastic optimization model for the supply chain of two biomass feedstocks (Jatropha and Paulownia), incorporating dual objectives of water consumption minimization and profit maximization. Their model also incorporated the water-energy nexus. Nugroho & Zhu (2024) [7] adopted a bi-level modeling approach for sourcing and transportation decisions in agricultural biomass supply chain, where multiple suppliers engage in competition to minimize operational costs and maximize their individual profits. Shirazaki et al. (2024) [1] proposed a two-stage scenario-based robust mixed-integer linear programming model for integrated microalgae supply chain network design and superstructure optimization problem. Gilani & Sahebi (2024) [10] developed a robust optimization model under uncertainty for third-generation feedstocks and non-edible biomass materials. Razm et al. [2025] [16] employed a data-driven robust optimization approach combined with machine learning to develop a multi-period, single-objective optimization model for profit maximization of two co-products: biodiesel and electricity. Recently, Gitinavard et al. (2025) [6] developed a mathematical model to minimize costs while accounting for demand uncertainty across multiple periods. They considered biofuels as the sole end product. The mentioned papers are summarized in Table 1.

Table 1. The literature review of related studies

Authors	Multi period	Multi objective	Network structure		Biomass generation	Final product	Water-energy nexus	Objective function				Solution method	Case study
			Forward	Closed-loop/ open loop				Minimizing cost Maximizing profit	Minimizing environmental impact	Maximizing energy	Other		
Ghelichi et al. (2018) [15]	✓	✓	✓		2	Biodiesel, Glycerin		✓	✓			Optimization software	✓
Babazadeh et al. (2019) [11]	✓		✓		2	Biodiesel, Glycerin		✓				Benders decomposition	✓
Mahjoub et al. (2020) [13]	✓	✓	✓		2,3	Biodiesel, Electricity		✓		✓		ε-constraint	✓
Afkhami & Zarrinpoor (2021) [12]	✓	✓	✓		2	Biodiesel, Glycerin, Biochar		✓	✓		✓	Torabi-Hassini method	✓
Yazdanparast et al. (2022) [14]	✓	✓	✓		2	Biofuel		✓	✓			Augmented ε-constraint	✓

Singh et al. (2023) [8]	✓	✓	✓		2	Biodiesel, Glycerin		✓	✓		✓	Augmented ε-constraint	
Rasekh et al. (2023) [4]	✓	✓	✓		2,3	Biodiesel, Electricity	✓	✓	✓	✓	✓	Goal programming	✓
Shirazaki et al. (2024) [1]			✓		3	Biofuel		✓				Optimization software	✓
Hosseinitabar et al. (2024) [3]	✓	✓	✓		2	Biofuel, Bioplastic, Glycerin	✓	✓			✓	Augmented ε-constraint	✓
Bahmani et al. (2024) [5]	✓	✓	✓		2	Biodiesel, Glycerin, Methanol, Biochar		✓			✓	Robust optimization	✓
Nugroho & Zhu (2024) [7]	✓	✓	✓		1	Hydrogen, Syngas		✓		✓		Branch and reduce	✓
Gilani & Sahebi (2024) [10]	✓	✓	✓		2,3	Microalgae, Jatropha	✓	✓	✓			Optimization software	✓
Gitinavard et al. (2025) [6]	✓		✓		2	Bioethanol		✓					✓
This paper	✓	✓		✓	2	Biodiesel, Electricity, Glycerin, Gas, Biochar	✓	✓		✓	✓	ε-constraint	✓

Our research methodology employed comprehensive searches across major academic databases, including Scopus, supplemented by targeted queries via Google Scholar to ensure a thorough review of relevant publications. As demonstrated in the literature review, while existing studies have extensively examined forward supply chain models, closed-loop supply chain network remain overlooked. The main contribution of this work addressed this gap by proposing a novel mathematical model for closed-loop biomass to bioenergy supply chain

3. Problem definition and mathematical modeling

The supply chain network investigated in this research comprises two levels: suppliers (i.e., Jatropha and Paulownia farms) and producers (biorefineries). One of the final products - biochar fertilizer produced during the anaerobic digestion process of biogas - is returned as a useful material to the beginning of the network, namely the Jatropha and the Paulownia farms.

The model specifically takes into account selectin of suppliers (Jatropha and Paulownia farms), transportation modes, and the amount of produced bioenergies to optimize the supply chain planning, The schematic of the supply chain structure is presented in Figure 1.

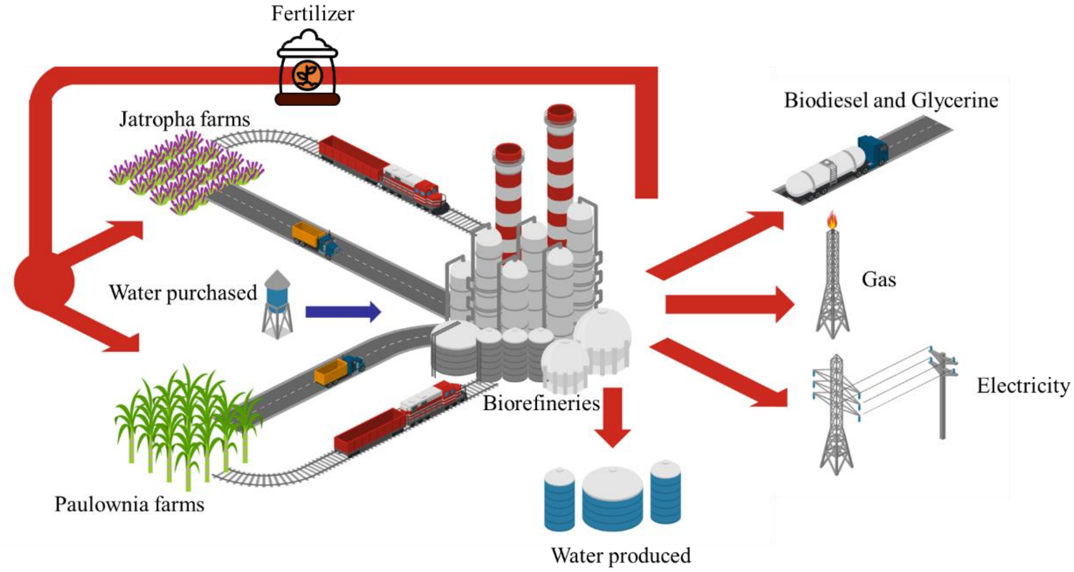

Figure 1. Structure of second-generation biomass supply chain based on Paulownia and Jatropha

The following table summarizes the sets, parameters, and variables employed in the problem formulation.

Sets	
I	Set of Jatropha farms $I\epsilon\{1,2,3,\dots,i\}$
J	Set of Paulownia farms $J\epsilon\{1,2,3,\dots,j\}$
L	Biorefineries $L\epsilon\{1,2,3,\dots,l\}$
M	Transportation modes $M\epsilon\{1,2,3,\dots,m\}$
t	Planning periods $T\epsilon\{1,2,3,\dots,t\}$
Parameters	
CH_{it}^{1}	Amount of Jatropha harvested from farm i in period t (ton)
CH_{it}^{2}	Amount of Paulownia harvested from farm j in period t (ton)
α	Conversion coefficient of Jatropha seeds into Jatropha oil (%)
CS_{i}^{1}	Cost of Jatropha farm i selection (million Toman)
CS_{j}^{2}	Cost of Paulownia farm j selection (million Toman)
PC_{it}^{1}	Purchasing cost per unit of Jatropha from farm i in period t (million Toman)
PC_{jt}^{2}	Purchasing cost per unit of Paulownia from farm j in period t (million Toman)
CB_{lt}	Production capacity of biodiesel in biorefinery l in period t (ton)
β	Percentage of seeds in Jatropha (%)
PCW	Cost of purchased water from water network (million Toman)
δ	Percentage of biodiesel derived from Jatropha seed oil (%)
CC_{lt}^{1}	Combustion gas capacity in biorefinery l in period t (m^3)
CC_{lt}^{2}	Combustion electricity capacity in biorefinery l in period t (MWh)
CBG_{lt}	Biogas production capacity in biorefinery l in period t (ton)
γ^{1}	Conversion coefficient of Jatropha branches and leaves and Paulownia to gas via combustion (m^3/ton)
γ^{2}	Conversion coefficient of Jatropha branches and leaves and Paulownia to water via combustion (lit/ton)
γ^{3}	Conversion coefficient of Jatropha branches and leaves and Paulownia to electricity via combustion (MWh$/ton$)
λ^{1}	Conversion coefficient of Jatropha branches and leaves and Paulownia to gas via biogas (m^3/ton)
λ^{2}	Conversion coefficient of Jatropha branches and leaves and Paulownia to electricity via biogas (MWh$/ton$)
λ^{3}	Conversion coefficient of Jatropha branches and leaves and Paulownia to fertilizer via biogas (%)
W^{1}	Water consumption per unit of biodiesel production (m^3/ton)
W^{2}	Water consumption per unit of biogas production (m^3/ton)
PF	Selling price of biochar to farms (million Toman)
D_{ilm}^{1}	Distance between Jatropha farm i and biorefinery l via transportation mode m (km)
D_{jlm}^{2}	Distance between Paulownia farm j and biorefinery l via transportation mode m (km)
TC_{m}	Unit transportation cost per unit of raw material via transportation mode m (million Toman)
CM_{lt}^{1}	Cost of converting Jatropha seeds to oil per unit in biorefinery l and period t (million Toman)
CM_{lt}^{2}	Cost of converting Jatropha branches and leaves and Paulownia to gas via combustion in biorefinery l and period t (million Toman)
CM_{lt}^{3}	Cost of converting Jatropha branches and leaves and Paulownia to electricity via combustion in biorefinery l and period t (million Toman)
CM_{lt}^{4}	Cost of converting Jatropha branches and leaves and Paulownia to water via combustion in biorefinery l and period t (million Toman)
CM_{lt}^{5}	Cost of converting Jatropha branches and leaves and Paulownia to gas via biogas in biorefinery l and period t (million Toman)

CM_{lt}^6	Cost of converting Jatropha branches and leaves and Paulownia to electricity via biogas in biorefinery l and period t (million Toman)
CM_{lt}^7	Cost of converting Jatropha branches and leaves and Paulownia to biochar via biogas in biorefinery l and period t (million Toman)
DB_t	Biodiesel demand in period t (ton)
DG_t	Glycerol demand in period t (ton)
DGS_t	Gas demand in period t (m^3)
DE_t	Electricity demand in period t (MWh)
PW	Selling price of water (million Toman)
M	A positive large number
Variables	
F_{iltm}^1	Amount of Jatropha transshipped from farm i to biorefinery l in period t via transportation mode m (ton)
F_{jltm}^2	Amount of Paulownia transshipped from farm j to biorefinery l in period t via transportation mode m (ton)
B_{lt}	Amount of biodiesel produced in biorefinery l and period t (ton)
G_{lt}	Amount of glycerol produced in biorefinery l and period t (ton)
BI_{lt}^1	Amount of Jatropha branches and leaves allocated for gas production via anaerobic digestion in biorefinery l and period t (ton)
BI_{lt}^2	Amount of Paulownia allocated for electricity production via anaerobic digestion in biorefinery l and period t (ton)
CG_{lt}	Amount of gas generated from combustion process in biorefinery l and period t (m^3)
CE_{lt}	Amount of electricity generated from combustion process in biorefinery l and period t (MWh)
BG_{lt}	Amount of gas generated from anaerobic digestion process in biorefinery l and period t (m^3)
BE_{lt}	Amount of electricity generated from anaerobic digestion process in biorefinery l and period t (MWh)
BF_{lt}	Amount of fertilizer generated from anaerobic digestion process in biorefinery l and period t (ton)
BW_{lt}^1	Amount of water purchased from water network for biogas production in biorefinery l and period t (m^3)
BW_{lt}^2	Amount of water purchased from water network for biodiesel production in biorefinery l and period t (m^3)
CW_{lt}	Amount of water produced from combustion process in biorefinery l and period t (m^3)
C_{lt}^1	Amount of Jatropha branches and leaves and Paulownia allocated for gas production via combustion in biorefinery l and period t (ton)
C_{lt}^2	Amount of Jatropha branches and leaves and Paulownia allocated for electricity production via combustion in biorefinery l and period t (ton)
WF_{lt}	Amount of water extracted in biorefinery l and period t (m^3)
x_{ilt}^1	A binary variable that equals 1 if Jatropha farm i allocated to biorefinery l in period t, and 0 otherwise.
x_{jlt}^2	A binary variable that equals 1 if Paulownia farm j allocated to biorefinery l in period t, and 0 otherwise.

The next part presents the problem modeling along with the objective functions and constraints:

$$\begin{aligned} Min\ Z_1 = {} & \sum_i\sum_l\sum_t CS_i^1 \times x_{ilt}^1 + \sum_j\sum_l\sum_t CS_j^2 \times x_{jlt}^2 + \sum_i\sum_l\sum_t\sum_m D_{ilm} \times TC_m \times F_{iltm}^1 \\ & + \sum_j\sum_l\sum_t\sum_m D_{jlm} \times TC_m \times F_{jltm}^2 + \sum_l\sum_t CM_{lt}^1 \times (B_{lt} + G_{lt}) + \sum_l\sum_t CM_{lt}^2 \times CG_{lt} \\ & + \sum_l\sum_t CM_{lt}^3 \times CE_{lt} + \sum_l\sum_t CM_{lt}^4 \times CW_{lt} + \sum_l\sum_t CM_{lt}^5 \times BG_{lt} \\ & + \sum_l\sum_t CM_{lt}^6 \times BE_{lt} + \sum_l\sum_t CM_{lt}^7 \times BF_{lt} + \sum_i\sum_l\sum_m\sum_t PC_{it}^1 \times F_{iltm}^1 \\ & + \sum_j\sum_l\sum_m\sum_t PC_{jt}^2 \times F_{jltm}^2 + \sum_l\sum_t (BW_{lt}^1 + BW_{lt}^2) \times PCW - \sum_l\sum_t PF \times BF_{lt} \\ & - \sum_l\sum_t PW \times WF_{lt} \end{aligned} \tag{1}$$

$$Max\ Z_2 = \sum_l\sum_t B_{lt} \tag{2}$$

$$Max\ Z_3 = \sum_l\sum_t G_{lt} \tag{3}$$

$$Max\ Z_4 = \sum_l\sum_t CG_{lt} \tag{4}$$

$$Max\ Z_5 = \sum_l\sum_t BG_{lt} \tag{5}$$

$$Max\ Z_6 = \sum_l\sum_t CE_{lt} \tag{6}$$

$$Max\ Z_7 = \sum_l\sum_t BE_{lt} \tag{7}$$

$$\sum_{l}\sum_{m} F^1_{iltm} \leq CH^1_{i,t} \quad \forall i,t \tag{8}$$

$$\sum_{l}\sum_{m} F^2_{jltm} \leq CH^2_{jt} \quad \forall t,j \tag{9}$$

$$\sum_{m} F^1_{iltm} \leq M \times x^1_{ilt} \quad \forall i,l,t \tag{10}$$

$$\sum_{m} F^2_{jltm} \leq M \times x^2_{jlt} \quad \forall i,l,t \tag{11}$$

$$B_{lt} \leq CB_{lt} \quad \forall l,t \tag{12}$$

$$G_{lt} \leq \frac{CB_{lt}}{10 \times \delta} \tag{13}$$

$$C^1_{lt} \leq CC^1_{lt} \quad \forall l,t \tag{14}$$

$$CBG_{lt} \leq BI^1_{lt} + BI^2_{lt} \quad \forall l,t \tag{15}$$

$$B_{lt} = \alpha \times \delta \times \sum_{i}\sum_{m} F^1_{iltm} \quad \forall l,t \tag{16}$$

$$G_{lt} = \alpha \times (1-\delta) \times \sum_{i}\sum_{m} F^1_{iltm} \quad \forall l,t \tag{17}$$

$$C^1_{lt} + C^2_{lt} + BI^1_{lt} + BI^2_{lt} = (1-\alpha)\left(\sum_{i}\sum_{m} F^1_{iltm} + \sum_{j}\sum_{m} F^2_{jltm}\right) \quad \forall l,t \tag{18}$$

$$CG_{lt} = C^1_{lt} \times \gamma^1 \quad \forall l,t \tag{19}$$

$$CW_{lt} + WF_{lt} = C^1_{lt} \times \gamma^2 \quad \forall l,t \tag{20}$$

$$CE_{lt} = C^2_{lt} \times \gamma^3 \quad \forall l,t \tag{21}$$

$$BG_{lt} = BI^1_{lt} \times \lambda^1 \quad \forall l,t \tag{22}$$

$$BE_{lt} = BI^2_{lt} \times \lambda^2 \quad \forall l, \tag{23}$$

$$BF_{lt} = (BI^1_{lt} + BI^2_{lt}) \times \lambda^3 \quad \forall l,t \tag{24}$$

$$W^1 \times B_{lt} \leq BW^2_{lt} + CW_{lt} - WF_{lt} \quad \forall l,t \tag{25}$$

$$W^2 \times (BI^1_{lt} + BI^2_{lt}) \leq BW^1_{lt} \quad \forall l,t \tag{26}$$

$$B_{lt} \geq DB_t \quad \forall l,t \tag{27}$$

$$G_{lt} \geq DG_t \quad \forall l,t \tag{28}$$

$$CG_{lt} + BG_{lt} \geq DGS_t \quad \forall l,t \tag{29}$$

$$CE_{lt} + BE_{lt} \geq DE_t \quad \forall l,t \tag{30}$$

$$F^1_{iltm}, F^2_{jltm}, B_{lt}, G_{lt}, BI^1_{lt}, BI^2_{lt}, CG_{lt}, CE_{lt}, BG_{lt}, BE_{lt}, BF_{lt}, BW^1_{lt}, BW^2_{lt}, CW_{lt}, C^1_{lt}, C^2_{lt}, WF_{lt}, WU^1_{lt} \geq \tag{31}$$

$$x^1_{ilt}, x^2_{jlt} \epsilon \{0,1\} \tag{32}$$

In the proposed model, the first objective function (1) minimizes the total supply chain costs, including supplier selection, farm-to-biorefinery transportation, production, plant procurement, and external water supply costs, while incorporating revenue from surplus water and fertilizer byproducts. The second through seventh objective functions (equations 2-7) respectively target maximization of: biodiesel and glycerol production, gas and electricity generation from combustion process and gas, electricity, and fertilizer production derived from biogas conversion.

In the constraints section, constraints (8) and (9) ensure that the maximum capacity limit of suppliers should not be violated, while constraints (10) and (11) ensure that the flow of raw materials can exist provided that the allocation of farms to biorefineries has been done. Furthermore, constraints (12)-(15) discuss about the production capacities. Eq. (16)-(17) compute the amounts of produced biodiesel and glycerol. constraints (19)-(24) shows that the energy production from each process equals the allocated feedstock quantity multiplied by the conversion factor. constraint (25) shows that the total amount of water produced in the combustion process and the water purchased from the water network must not be less than the water required for biodiesel production. constraints (26) states that the water consumption in the anaerobic digestion process must not exceed the volume of purchased water. constraints (27)-(30) indicate that each type of produced energy must meet its corresponding demand. constraints (30)-(32) specify the types of the decision variables.

4. Computational results and analysis

4.1 case study

Given the adaptive characteristics of Jatropha and Paulownia, notably their drought tolerance, ability to thrive in marginal soils, and resilience to diverse climatic conditions, we selected these feedstocks for our study. This selection aligns with the abundance of underutilized semi-arid and barren lands in southern and southeastern Iran and with the additional objective of meeting a portion of the regional energy demand through localized biofuel production, thereby reducing reliance on fossil fuels and enhancing energy security in these areas where water scarcity and soil salinity limit conventional agriculture.

The selected Jatropha farms are located in six provinces: Fars, Kohgiluyeh va Boyer-Ahmad, Chaharmahal va Bakhtiari, Khuzestan, Yazd, and Isfahan. Similarly, the Paulownia farms span five provinces: Fars, Hormozgan, Kohgiluyeh va Boyer-Ahmad, Chaharmahal va Bakhtiari, and Khuzestan.

For biorefineries, Yazd, Isfahan, and Fars provinces are selected as the second tier of the network. Additionally, two transportation modes - truck and rail - are considered to create links between these two levels. The model utilizes half-yearly time periods for operational planning. Table 2 summarizes the plausible parameter ranges which were employed in the model implementation and solution process.

Table 2. Parameters and their ranges

Parameter	Range/Value	Parameter	Range/Value
CH_{it}^1	[8,11]	W^1	[1,4]
CH_{it}^2	[4,7]	W^2	[2,7]
CS_i^1	[25,35]	D_{ilm}^1	[98,941]
CS_j^2	[35,50]	D_{jlm}^2	[98,830]
PC_{it}^1	[3,6]	TC_m	[0.003,0.005]
PC_{jt}^2	[11,13]	CM_{lt}^1	[13,17]
CB_{lt}	[3,5]	CM_{lt}^2	[7,10]
CC_{lt}^1	[1,4]	CM_{lt}^3	[10,14]
CC_{lt}^2	[1,2]	CM_{lt}^4	[4,7]
CBG_{lt}	[1,3]	CM_{lt}^5	[16,20]
α	[0.25,0.5]	CM_{lt}^6	[20,24]
β	[0.30,0.45]	CM_{lt}^7	[9,12]
PCW	[4,10]	DB_t	[1600,1900]
δ	[0,1]	DG_t	[1800,2100]
γ^1	[100,500]	DGS_t	[800,1100]
γ^2	[500,0.06]	DE_t	[800,1100]
γ^3	[0,1]	PW	[3,5]
λ^1	[100,150]	PF	[50,100]
λ^2	[0.33,0.66]	M	[10000,1000000]
λ^3	[0,1]		

4.2. Results and discussion

Given that, the proposed mathematical model is multi-objective, a multi-objective decision-making solution method should be applied to solve the problem. Hence, at first the objectives 2-7 (equations. (2)-(7)) were aggregated into a single unified objective function by a normalization approach to overcome different energy units. The integrated objective function related to energy is as follows:

$$Z' = \frac{\sum_l \sum_t B_{lt}}{Z_2^*} + \frac{\sum_l \sum_t G_{lt}}{Z_3^*} + \frac{\sum_l \sum_t CG_{lt} + \sum_l \sum_t BG_{lt}}{Z_4^* + Z_5^*} + \frac{\sum_l \sum_t CE_{lt} + \sum_l \sum_t BE_{lt}}{Z_6^* + Z_7^*} \tag{33}$$

Z_k^* denotes the optimal value of objective function k $(k = 2, \dots, 7)$ Subsequently, the presented bi-objective problem was solved using the ε-constraint method implemented in GAMS 24.1.3 (using CPLEX solver). Computational experiments were conducted on a high-performance computing system (Intel(R) Core (TM) i7-6600U CPU @ 2.60GHz 2.80 GHz and RAM 16.0 GB) to handle the model's complexity.

One of the classic and widely used methods for solving multi-objective optimization problems is the ε-constraint method. In this approach, instead of optimizing multiple objective functions simultaneously, one function is selected as the primary objective, while the others are incorporated into the model as constraints. This transforms the multi-objective problem into a set of single-objective optimization problems. Consider a multi-objective optimization problem defined as follows:

$$min\ \left(f_1(x), f_2(x), \dots, f_k(x)\right)$$
$$subject\ to\ x \epsilon X$$

For implementing ε-constraint method, we will have:

$$\min\left(f_1(x)\right)$$
$$subject\ to:$$

$$f_2(x) \leq \varepsilon_2, \dots, f_k(x) \leq \varepsilon_k$$
$$x \epsilon X$$

Here, ε_k $k \epsilon [1, k]$ represent parameters whose values are varied within specified interval constructed by optimal and nadir points:

$$\varepsilon_k = Z_k^{andir} + \left(\frac{Z_k^* - Z_k^{andir}}{q_k}\right) \times n_k \quad n_k = 1, 2, \dots, q_k \tag{34}$$

Where, the domain of each objective function k is divided to q_k equal intervals. By solving this model for different values of ε, a set of Pareto-optimal solutions is obtained.

Based on the model solution outputs, Figure 2, clearly demonstrates the optimal procurement strategy for each biorefinery, specifying which Jatropha and Paulownia farms should supply raw materials during each planning period.

Figure 2. Structure of second-generation biomass supply chain based on Paulownia and Jatropha.

Figure 3 presents a Pareto front illustrating the trade-off between two competing objective functions: cost minimization (Z_1 on the horizontal axis) and the aggregated energy objective function (Z' on the vertical axis). The yellow points form the Pareto frontier, representing optimal solutions where neither objective can be improved without sacrificing the other. As Z_1 increases (moving rightward), higher energy production (Z') is achieved, revealing a direct but conflicting relationship - reducing costs limits energy output, while maximizing production increases costs. The leftmost points minimize costs, whereas the rightmost points maximize energy output, with the optimal choice depending on the decision-maker's priorities between economic efficiency and production capacity

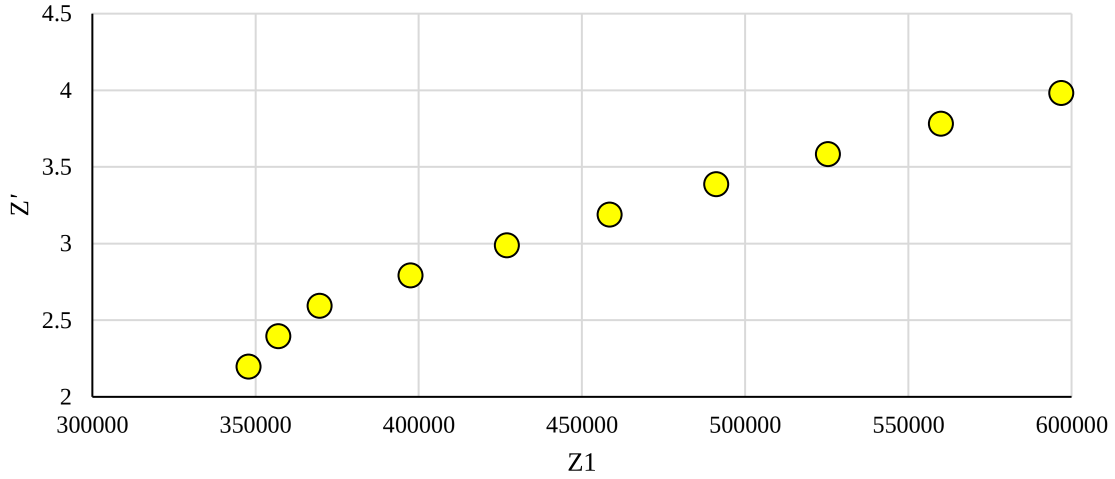

Figure 3. Pareto front

Figure 4 presents a detailes the share of cost and revenue items of the studied supply chain network, categorizing (1) incurred costs and (2) revenue streams from fertilizer and surplus water sales. Notably, water procurement costs and farm leasing expenses are not shown due to their negligible impact (<1% of total costs) relative to other expenditure components. As deicted, procurement costs rank fisrst with 62% share in total cost and productin costs is in the next position.

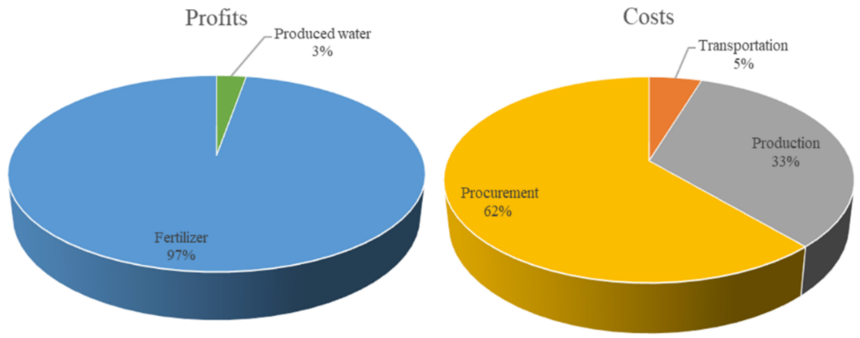

Figure 4. Costs and revenues of the supply chain

In the following, a sensitivity analysis is conducted on two of the model's main parameters, and the results are explained. As demonstrated in Figure 5, we systematically varied the biodiesel production capacity within the $[-100\%, 400\%]$ range to evaluate its impact on objective function Z_2, which representsthe amount of total biodiesel production. The analysis shows the biodiesel production increases as we expand capacity, starting from zero at minimum capacity (-100%) until reaching a maximum level where it can't grow further due to supplier’s capacity limitations.

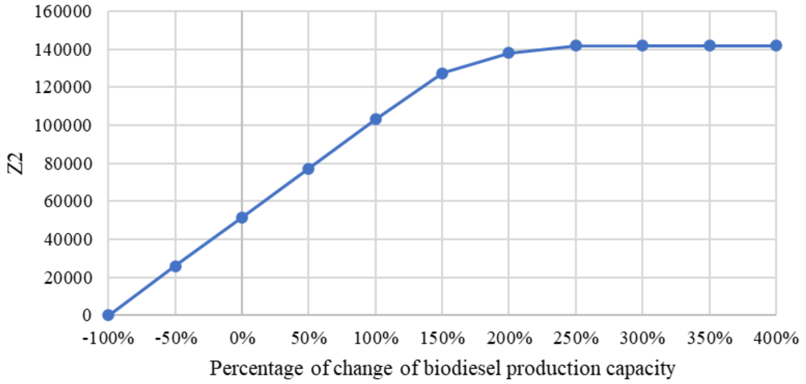

Figure 5. Investigating the effect of changing the biodiesel production capacity on the Z_2

Figre 6 depicts the impacts of changing demands on the total ost. As demand decreases to -100% (as shown in the chart), Z_1 reaches zero since the supply chain ceases production, consequently reducing all costs to zero. Conversely, increasing demand to $+100\%$ raises costs. Exceeding this value makes the model infeasible due to either production capacity limitations or supplier capacity constraints.

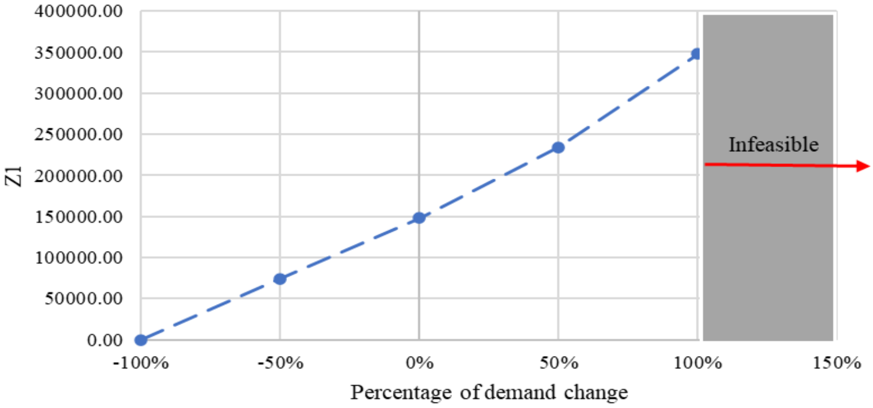

Figure 6. Sensitivity analysis on demands

Figure 7 clearly illustrates that implementing a closed-loop supply chain in the network can have a significant impact on reducing network costs. In the closed-loop supply chain, while the values of Z' remain constant, the values of Z_1 have experienced a considerable increase.

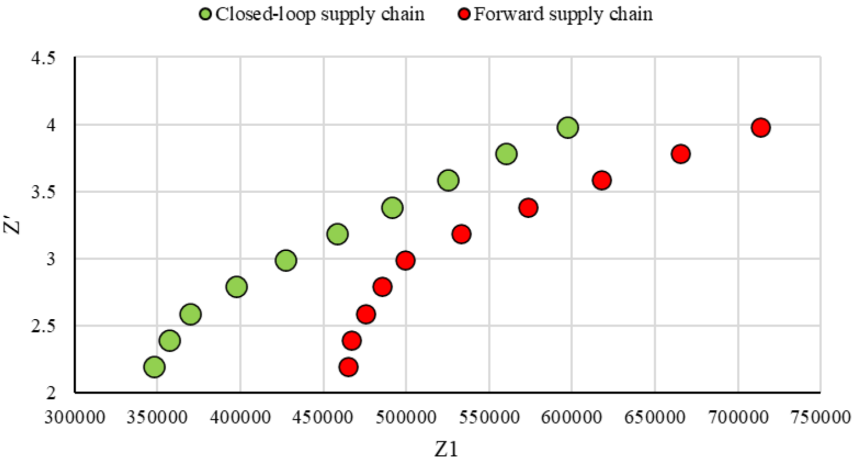

Figure 7. Comparing closed loop and forward supply chains based on the values of objective functions

5. Conclusion

This paper investigated a closed-loop supply chain for converting biomass feedstocks (Jatropha and Paulownia) into multiple products including electricity, biogas, fertilizer, biodiesel, and glycerol. Our literature review revealed a critical research gap in closed-loop systems for this process, prompting the development of a novel supply chain model. The proposed multi-objective model was solved using the epsilon-constraint method with real-world data in Iran. The comparative analysis of closed-loop versus traditional supply chain configurations demonstrated he superiority of closed-loop structure. Sensitivity analyses were conducted on both demand fluctuations and biodiesel production capacity. Future research directions include: incorporating uncertainty in supply, demand and the capacity parameters, applying exact or metaheuristic solution approaches for solving the problem in large sizes and expanding the supply chain echelons.

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