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Scenario-Based Mathematical Modeling for Biofuel Supply Chain Design

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ABSTRACT

Objective: This study aims to design and optimize a sustainable biofuel supply chain focusing on water resource management, uncertainty reduction, and enhancing economic, environmental, and social performance. Sustainable biomass, such as Paulownia trees, and recycled water are considered key inputs, providing an integrated solution to the challenges posed by fossil fuels and the urgent need for renewable energy development.

Methods: A multi-objective mathematical model is proposed to minimize costs, satisfy demand, and mitigate environmental impacts. The model incorporates uncertainties in supply and demand using the LP-metric method and applies the Fuzzy Analytic Hierarchy Process (FAHP) to weight objectives, ensuring balance among conflicting goals. Sensitivity analysis examines variations in biomass supply, prices, and demand, while Pareto frontier analysis evaluates trade-offs across objectives.

Results: Results show that scenario-based modeling enables a comprehensive assessment of supply and demand impacts on supply chain performance. Incorporating wastewater and sewage sludge reduces pressure on natural resources and improves economic and environmental efficiency. The ε-constraint method generates Pareto-optimal solutions, offering decision-makers alternatives consistent with their priorities. Sensitivity analysis highlights that using Paulownia biomass and recycled water enhances flexibility, reduces risks, and promotes balance among economic, environmental, and social objectives, while lowering costs and unmet demand.

Conclusion: This study provides a practical framework for designing and managing a sustainable biofuel supply chain by presenting a comprehensive and practical model. The findings can serve as a roadmap for developing renewable energy and resource efficiency in the energy sector. Additionally, the proposed model offers a robust decision-making tool under conditions of uncertainty and environmental and economic fluctuations. Its application can significantly support sustainable development policies and reduce dependence on fossil fuel resources.

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Introduction

Fossil fuels, characterized by their finite reserves and uneven distribution, account for a significant share of the global energy system and represent the primary source of greenhouse gas (GHG) emissions. Nevertheless, increasing energy demand, security concerns, the climate crisis, and the economic attractiveness of renewable resources have drawn growing attention to renewable energy (RE) as an alternative and sustainable source, playing a vital role in carbon reduction (Ghorbani et al., 2020). Among these resources, biomass has emerged as an appealing option and a sustainable substitute for conventional energy carriers such as coal, oil, and natural gas, due to its worldwide availability, favorable storage capabilities, and considerable potential (Wang & Hong, 2024). In Iran, the intensity of energy consumption and heavy reliance on fossil fuels are significantly higher than the global average, a situation that not only imposes substantial economic burdens but also results in serious environmental consequences, including air pollution and the rising emission of greenhouse gases (Kazemi et al., 2023).

The limitations of fossil fuel resources and the environmental challenges associated with greenhouse gas emissions have necessitated the search for new and sustainable energy sources, particularly in energy-intensive sectors such as industry (Pandey et al., 2016). Heavy reliance on fossil fuels has increased greenhouse gas concentrations, especially carbon dioxide (CO_2), resulting in global warming (Rashid Khan et al., 2021). One of the most effective solutions for mitigating these environmental impacts is the adoption of biofuels, which are produced from renewable resources such as biomass. Biofuels, including bioethanol, biodiesel, and bio-jet fuels, are derived from cellulose-based organic compounds, primarily extracted from plants and agricultural products (Murillo-Alvarado & Ponce-Ortega, 2024).

Biofuels, by capturing CO_2 during the cultivation process and exerting lower environmental impacts than fossil fuels, represent the largest renewable energy source. They can reduce dependence on fossil fuels and significantly mitigate greenhouse gas emissions (Koçar & Civaş, 2013). Depending on their production sources, biofuels can be categorized into different generations, as illustrated in Figure 1 (Gomez et al., 2011).

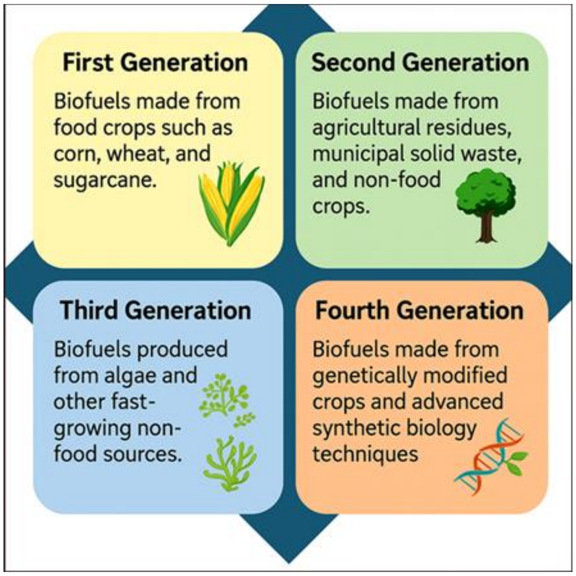


Figure 1. Different generations of biofuels

Among these, bioethanol and biodiesel are recognized as the most widely used biofuels, whereas bio-propane and bio-butane have received less attention (Seidl & Goulart, 2016). Numerous studies have investigated biomass feedstocks for biofuel production, including wheat straw, corn, sugarcane, and vegetable oils. At the same time, plants such as cactus and agave have also been identified as potential sources. However, most research has focused on food-based biomass such as corn and sugarcane, which may pose future challenges to the food industry. Therefore, exploring biochemical pathways and identifying non-food biomass sources that can be readily converted into fuels are essential for improving the biofuel supply chain and advancing sustainable energy development (Murillo & Ponce, 2024).

With their unique characteristics, Paulownia trees have emerged as one of the most promising biomass resources for bioenergy production. This fast-growing tree can thrive in poor soils and harsh environmental conditions, making it suitable for cultivation across diverse geographical regions (Ghadge et al., 2020). Recent studies on the design of biofuel supply chain networks have demonstrated that using such non-food feedstocks not only alleviates pressure on agricultural resources but also enhances the overall sustainability of the supply chain (Mohammadi et al., 2022). Paulownia can reach maturity quickly and produce substantial volumes of woody biomass, rendering it a sustainable and practical resource for biofuel production. In addition, due to its high carbon dioxide absorption capacity, Paulownia is vital in reducing greenhouse gas emissions. It is regarded as an environmental solution for addressing climate change. Resistance to pests, low irrigation requirements, and reduced operational costs are further advantages that position Paulownia as an ideal feedstock for the biofuel supply chain (Abbasi & Pishvaee, 2019).

With its strategic location and abundant natural resources, Iran possesses significant potential for renewable energy production, particularly biomass, which can contribute to meeting energy demands and reducing dependence on fossil fuels. However, despite its vast fossil and non-fossil energy resources, the Iranian energy sector—especially the electricity industry—faces considerable challenges (Iranian Ministry of Energy, 2018). Air pollution, primarily caused by excessive fossil fuel consumption, has positioned Iran among the world's top ten greenhouse gas emitters (International Energy Agency, 2021). Consequently, Iran's fossil fuel–based economy needs to be replaced with a more resilient and sustainable energy industry (Mollahosseini et al., 2017).

The biofuel supply chain network (BSCN) is a complex, multi-stage process that begins with the initial production of biomass and extends to the final distribution of fuels to consumers. Each stage requires optimization to enhance responsiveness or minimize costs (Qadir et al., 2021). The chain faces critical challenges, including ensuring a sustainable supply of feedstock, improving the efficiency of conversion processes, and designing effective distribution systems, all of which are vital for achieving sustainable biofuel development (Ramirez et al., 2019). Developing the biofuel supply chain with a strong focus on sustainability, supported by the integration of life cycle assessment (LCA) to address environmental and social dimensions, through a multi-objective optimization model, ensures the capacity of the network to meet the needs of future generations (Jakubowski, 2022).

In addition to sustainability considerations, biofuel energy systems are highly dependent on water resources. Therefore, applying innovative decision-making approaches, such as fuzzy cognitive maps, for analyzing the interactions between water and energy can provide a more comprehensive and practical perspective on the sustainability of these systems (Ghasemi et al., 2019). Optimizing decision-making in such systems requires thoroughly understanding their interactions and interrelationships with water resources (Yousefloo et al., 2023). Water plays a fundamental and critical role in biofuel production and in processes such as biomass cultivation, infrastructure development, cooling systems, and energy generation (Zhang & Vesselinov, 2016). Using municipal and industrial wastewater to supply water for biofuel networks can significantly reduce their dependence on freshwater resources while reinforcing the interconnection between water and energy systems (Zema et al., 2012). Nevertheless, additional challenges—such as financial constraints and political, economic, and managerial issues—have hindered progress in renewable energy projects (Jana et al., 2022).

To overcome these challenges, multi-objective optimization based on fuzzy logic—capable of modeling uncertainty—can lead to more realistic decision-making in supply chains (Ransikarbum & Pitakaso, 2024). In a recent study, Mohseni and Mohammadi (2025) demonstrated that applying fuzzy multi-objective programming methods in designing energy supply networks can improve decision-making under uncertainty and enhance supply chain resilience. By incorporating vague and imprecise data, fuzzy logic enables decision-makers to design more flexible networks while simultaneously reducing costs and emissions, thereby playing a critical role in improving the efficiency and sustainability of energy systems (Jana et al., 2022).

This study aims to design and optimize a localized biofuel supply chain in Iran, employing fuzzy logic and water resource management to enhance economic, environmental, and operational sustainability. Using Paulownia biomass and forest wood residues, combined with intelligent water resource management, is targeted at reducing environmental impacts while improving financial efficiency. Dynamic facility location, warehouse risk management, and scenario-based supply and demand analysis under a fuzzy approach contribute to developing a flexible and sustainable supply chain that addresses environmental and economic requirements by leveraging local capacities.

The remainder of this paper is structured as follows. Section 2 provides a detailed review of the theoretical foundations and prior literature, including studies on bioenergy supply chains, multi-objective decision-making frameworks, water resource management issues, and approaches for addressing uncertainty. Section 3 presents the conceptual framework and introduces the model developed in this study, along with the analytical methods and tools employed. Section 4 discusses and analyzes the results obtained from implementing the model. Finally, Section 5 concludes the paper by summarizing the key findings, outlining practical implications, and suggesting directions for future research.

Literature Background

Theoretical Background

Given the dominant share of fossil fuels in the national energy mix and the growing need for sustainable alternatives, the biofuel supply chain in Iran has gained particular significance. This chain, which encompasses all stages of biomass production, processing, and transportation, faces more complex and unique challenges than many other countries due to the country’s specific climatic conditions and water resource limitations (Mohammadi et al., 2022).

The biofuel supply chain is a complex network comprising the production, transportation, and distribution of renewable fuels, and its optimization has become increasingly important for advancing sustainable development and reducing environmental impacts (Zhou et al., 2024). The network includes upstream, midstream, and downstream processes. In the upstream stage, biomass is cultivated in farms and preprocessed at specialized facilities to reduce volume and facilitate transportation. Dense biomass is transported to refineries or biogas facilities via different logistics modes. Finally, downstream processes are carried out to produce gasoline-equivalent products or to distribute electricity generated from biogas products (Habibi et al., 2023).

The biofuel supply chain faces multiple challenges, including the sustainable supply of feedstock, high production and processing costs, market and price fluctuations, and issues related to transportation and storage. These challenges clearly highlight the necessity of adopting innovative and integrated approaches for effective management and optimization of the supply chain (Datta et al., 2019). In Iran, the dispersion of biomass resources and the weakness of energy transportation infrastructure are among the most significant barriers to developing the biofuel supply chain (Abbasi et al., 2021; Qadir et al., 2021).

The biofuel supply chain, due to its reliance on renewable natural resources, the environmental issues associated with production and conversion processes, and the inherent uncertainties in feedstock supply, is considerably different from other supply chains and requires specific approaches for optimization and sustainability management (Abbasi et al., 2021). Managing and mitigating risks in every business context is one of the most significant challenges in today's supply chains. Risk management is also unavoidable in the biofuel supply chain (Wachyudi et al., 2020). Since natural and climatic factors directly affect biomass resources, risk management enables predicting and mitigating potential disruptions, thereby ensuring the sustainability and efficiency of the energy supply system (Zarei et al., 2022).

Risk management in the face of uncertainty is also considered essential (Zhou et al., 2024). In Iran, fluctuations in rainfall and recurring droughts have significantly increased the risk of biomass supply. Therefore, employing tools such as scenario planning and fuzzy models to analyze climatic and market impacts is even more critical compared to developed countries (Zarei et al., 2022). Uncertainty is an inherent characteristic of the biofuel supply chain, arising from various factors such as market fluctuations, climate variability, challenges in feedstock supply, and inaccurate forecasts of demand and consumption patterns. These uncertainties directly affect the performance and sustainability of the supply chain (Gital & Bilgen, 2024). Accordingly, using probabilistic models, scenario planning, and multi-objective optimization can assist in predicting and mitigating risks, thereby enhancing the resilience and sustainability of the system (Habib & Huang, 2024).

Water resources play a fundamental role in biofuel production processes, as a significant share of water is consumed in biomass cultivation, conversion processes, and system cooling (Yousofloo et al., 2023). However, challenges such as declining water resources, the adverse impacts of climate change, and increasing competition among industrial sectors for water use pose serious threats to the sustainability of these supply chains (Zhang et al., 2016). Using recycled water and non-freshwater sources can serve as suitable options for meeting water demands in these processes (Zama et al., 2012). Moreover, the complex interrelationship between water and energy in biofuel production implies that any optimization in one area can have significant effects on the other; thus, managing this nexus is of particular importance for reducing costs and enhancing sustainability (Murillo-Alvarado & Ponce-Ortega, 2024). In Iran, which is considered one of the highly waterstressed countries, the dependence of bioenergy processes on water resources creates an even greater challenge. Therefore, using industrial and municipal wastewater to cultivate energy crops can be a localized and effective solution (Yousofloo et al., 2023).

Sustainable optimization of the biofuel supply chain has gained increasing importance as a key solution for addressing environmental crises, climate change, and the depletion of fossil resources, while supporting the provision of clean energy and reducing pollution (Wang & Hong, 2024). By emphasizing the balance among economic, environmental, and social objectives, this approach offers a comprehensive framework for efficient resource management and mitigating adverse environmental impacts such as greenhouse gas emissions. In this context, social objectives—such as creating sustainable employment, empowering local communities, and ensuring equitable distribution of benefits—play a pivotal role in improving quality of life and advancing sustainable development (Ramírez-Arpide et al., 2019).

Various biofuel supply chain models have been developed as key tools for achieving sustainability. These models aim to optimize feedstock supply, production, and distribution processes, thereby reducing costs, lowering greenhouse gas emissions, and enhancing efficiency (Jana et al., 2022). Multi-objective models effectively balance economic, environmental, and social goals. Moreover, probabilistic and fuzzy models are widely applied to manage uncertainties. In contrast, spatio-temporal models, using tools such as Geographic Information Systems (GIS) for optimal facility location, further contribute to efficient supply chain management and sustainable development (Habib & Huang, 2024).

Practical Background

Extensive research has been conducted on the challenges of the biofuel supply chain and strategies to address them. Paul et al. (2024) examined the challenges associated with the commercialization of biofuels, including high production costs, feedstock price fluctuations, and market uncertainties. They emphasized the importance of adopting advanced technologies and supportive policies to enhance economic sustainability in this field. Wassie (2020) analyzed issues related to land cultivation and access to biological resources. Pan et al. (2024) studied greenhouse gas emissions and their environmental impacts. Abbasi et al. (2021) investigated the high transportation costs, while Qadir et al. (2021) highlighted the infrastructural requirements and necessities.

Researchers have addressed this issue in studies focused on risk management in the biofuel supply chain. In their research, Zhou et al. (2024) examined risks arising from market uncertainties, including feedstock price volatility and demand fluctuations, which are crucial in supply chain sustainability. Langholtz et al. (2024), using a climate risk management framework, assessed the impact of drought on biomass production and the costs of the biofuel supply chain, emphasizing the importance of advanced technologies and improved logistics in reducing vulnerabilities. Ali and Govindan (2023) also studied the role of transformation in reducing operational risks in the agri-food supply chain, demonstrating that adopting Industry 4.0 technologies can effectively mitigate supply chain disruptions, including financial and transportation challenges.

Scenario planning, simulation, and applying probabilistic and fuzzy models have been widely recognized as practical tools for predicting and mitigating uncertainty. Through mathematical modeling, Huang et al. (2024) investigated the impact of technological choices and uncertainty management on enhancing the sustainability and efficiency of the bioethanol supply chain. Wang et al. (2024), by integrating the GIS-MCDM method with quantile scenario analysis, examined the optimization of the bioethanol supply chain and demonstrated that optimal facility location and resource management, under conditions of uncertainty and with governmental support, can effectively meet bioethanol demand.

Fuzzy programming is another popular approach for addressing uncertainty. Mondal et al. (2023), by combining the DEMATEL method with a robust fuzzy-stochastic programming framework, proposed a model for optimizing the biofuel and bioenergy supply chain. This model improves the supply chain's sustainability and efficiency by analyzing causal relationships and incorporating uncertainty.

Multi-objective modeling, emphasizing sustainability and other key aspects of the biofuel network, has recently attracted significant attention as an effective tool for optimizing and managing the supply chain. Bahmani et al. (2024), by proposing a multi-objective optimization model, examined the design and management of the biodiesel supply chain under disruption conditions. Their findings showed that by applying optimal strategies, the impacts of disruptions can be mitigated, costs can be managed, and supply chain resilience can be enhanced.

Arabi and Yaghoubi (2024), using a Lagrangian approach and a bi-objective model under uncertainty; Huang et al. (2024), through mathematical modeling and robust optimization; and Zhou et al. (2024), by applying a mixed-integer linear programming (MILP) model, have all investigated the design and optimization of the biofuel supply chain. These studies emphasize critical aspects such as uncertainty, resilience, and sustainability in supply chain management.

Zarrinpour et al. (2021), in their study, proposed a model that incorporates uncertainties by applying fuzzy interactive programming and the fuzzy best–worst method for weighting. Similarly, under uncertainty, Bayramzadeh and Saeedi (2019) examined a multi-objective possibilistic programming model for the second-generation biomass supply chain.

Metaheuristic techniques have also emerged as modern approaches for designing and optimizing the biofuel supply chain, offering practical solutions to address complex and multi-objective problems under constraints and uncertainty. Suresh et al. (2024), by optimizing artificial neural network (ANN) models with metaheuristic algorithms, provided accurate predictions of biodiesel engine emissions. Their results indicated reductions in carbon monoxide (CO), unburned hydrocarbons (HC), and smoke, but an increase in nitrogen oxides (NOx), thereby underscoring the importance of such methods in improving biofuel supply chain performance. Maharana et al. (2023) optimized the biofuel supply chain network by developing a nonlinear mathematical model and applying a particle swarm optimization (PSO) algorithm. Their model effectively managed flow rate and capacity constraints by employing a repair operator, reducing total costs and enhancing supply chain performance. Table 1 summarizes prior biofuel supply chain optimization research, focusing on mathematical modeling, sustainability dimensions, and approaches for handling uncertainty.

Table 1. Summary of biofuel supply chain studies

Sources	Type of Biofuel	Model Type	Sustainability			Coping with water resource constraints	Uncertainty modeling approach	Uncertainty parameters	Application/Innovation
			Eco	Env	Soc				
(Mohseni & Mohammadi, 2025)	Forest waste	Fuzzy Multilayer	●	●	●	--	Fuzzy	Supply and Demand	Promoting Sustainability in the Biofuel Chain with a Fuzzy Approach
(Fathi et al., 2024)	--	Fuzzy multi-objective	●	●	●	--	Fuzzy	Demand	NSGA-II and MOPSO meta-heuristic algorithms and Pareto front analysis
(Murillo-Alvarado & Ponce Ortega, 2024)	Mixed Sources	Multi-Objective	●	●	--	--	--	--	Reducing costs and greenhouse gas emissions
(Rahmandoost et al., 2023)	Municipal waste	Robust multi-objective + meta-heuristic	●	●	●	--	Robust	Demand	Reducing collection costs and pollution
(Islampanah et al., 2023)	Industrial waste	Inverse network design (VANET)	●	●	--	--	--	Capacity/Carrying Cost	Using VANET in Reverse Logistics
(Ghozatfar & Yaqoubi, 2023)	Municipal Solid Waste	Single Objective	●	--	--	--	--	Conversion Rate Factor	Focus on reducing processing costs
(Yousefloo & Babazadeh, 2023)	Municipal Solid Waste	Multi-Objective	●	●	●	Water Saving	Random	--	Emphasis on Optimal Water Consumption in the Chain
(Mohammadi et al., 2022)	--	Two-Objective	●	--	--	Water consumption	--	--	Internet of Things (IoT), Radio Frequency Identification (RFID), and

									Blockchain in the Supply Chain
(Abdali & Sahebi, 2021)	Sugarcane	Multi-Objective	●	●	--	Water Consumption	--	--	Integrating Water, Energy, Food, and Land in the Sugarcane Supply Chain
(Gilani & Sahebi, 2020)	Sugarcane	Multi-Objective	●	●	●	--	Robust Optimization	Demand, Price	Sustainable Design of the Sugarcane-Bioethanol Chain
(Mahjoub et al., 2020)	Jatropha, microalgae	Multi-Objective	●	●	--	--	Robust Optimization	--	Second and third generation chain with a multi-objective model
(Mohammadi, Alem Tabriz & Pishvaee, 2018)	--	Fuzzy multi-objective (green closed loop)	●	●	●	--	Fuzzy	Fuzzy Constraints	Integrating Financial Decisions in the Green Model
(Petridis et al., 2018)	Agricultural Waste	Multi-Objective	●	●	●	--	--	--	Sustainable biomass chain with ideal planning
(Mohseni & Pishvaei, 2016)	Microalgae	Multi-Objective	●	●	--	--	Robust Optimization	Cost and Demand	Algae–Biofuel Chain with Solid Planning
(Zhang et al., 2016)	Edible oil	Single-Objective	●	--	--	--	--	--	Robust optimization of the waste oil (WCO)-based biodiesel chain
Current Research	Paulownia Tree and Forest Waste	Multi-Objective	●	●	●	Wastewater Resources	Random	Supply and Demand	Paulownia Biofuel Chain with Fuzzy Multi-Objective Approach and Water Management

A review of previous studies indicates that although extensive research has been conducted on optimizing biofuel supply chains, many of these studies have addressed only limited aspects of sustainability. Less attention has been given to the optimization and integrated management of water resources, and Paulownia biomass—despite its high potential—has been rarely studied. To bridge these gaps, this research introduces the following innovations:

- Proposing a comprehensive and integrated approach: Designing a biofuel supply chain incorporating sustainable water resource management while addressing economic, social, and environmental sustainability.
- Focusing on Paulownia biomass: Examining Paulownia as a promising yet underexplored feedstock for biofuel production.
- Incorporating wastewater and sludge treatment into the supply chain: Utilizing these resources as part of a circular economy to improve efficiency and minimize resource wastage.

- Warehouse risk management: Developing strategies to reduce warehouse vulnerability in the face of environmental and economic uncertainties.
- Enhancing supply chain resilience: Improving supply chain flexibility against environmental changes and challenges arising from uncertainty.

Materials and Methods

Due to its complex nature and dependence on natural resources, the biofuel supply chain is influenced by uncertainties such as climate change, market fluctuations, and resource constraints. Therefore, designing a comprehensive multi-objective model for its optimization is essential. This study develops a multi-objective mathematical model that integrates stochastic and fuzzy approaches, enabling more accurate analysis of uncertainties and supporting improved decision-making under real-world conditions. The model simultaneously focuses on economic sustainability, warehouse risk management, water resource management, and environmental performance enhancement.

In this model, uncertainties in supply and demand—such as unpredictable variations in biomass production volume, market demand fluctuations, price changes, and environmental factors including weather conditions and natural disasters—are explicitly considered. Facility-related costs are also modeled using fuzzy logic to provide greater flexibility in decision-making. The objective functions of the model are designed to minimize total costs, reduce carbon emissions, and optimize economic and environmental impacts. Moreover, by managing warehouse-related risks, the model prevents delays or disruptions in biofuel supply, ensuring reliable access. Reducing unmet demand lowers dependence on more polluting or costly alternatives, thus generating positive social and environmental outcomes.

The proposed biofuel supply chain structure is illustrated in Figure 2. This model consists of five tiers, including farms with primary drying units, two types of warehouses equipped with secondary drying units, preprocessing (conversion) centers, biogas facilities, and final consumers. In addition, water treatment centers are included to provide the required water for farms and facilities, and two types of vehicles with different capacities are employed for transportation.

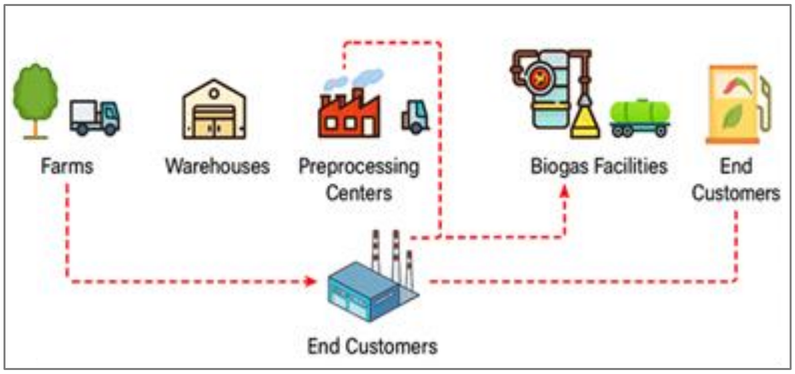


Figure 2. Proposed structure of biofuel supply chain model

The biomass utilized—consisting of wood residues and Paulownia trees—is harvested directly from farms, where its initial moisture content is reduced using on-site drying units before being transported to storage facilities. Two types of warehouses, namely constructible and rental, with varying capacities, are considered. The secondary moisture of the biomass is further reduced by drying units installed in the warehouses, ensuring optimal conditions for subsequent preparation stages. After storage and moisture reduction, the biomass is transported to preprocessing centers, where final preparations such as shredding and optimization for energy production are carried out. The processed materials are then delivered to biogas facilities, where they undergo refining processes and are converted into clean energy. The electricity generated through this process is transmitted directly to consumers, serving as a sustainable and renewable energy source to meet demand.

The water required for the supply chain is sourced from recycled resources, including municipal wastewater and sewage sludge. This approach reduces reliance on freshwater resources and generates additional economic and environmental benefits by producing organic fertilizers during treatment. Water consumption and fertilizer production are modeled for sustainability analysis as stochastic variables.

Two types of vehicles—trucks and trailers with different capacities—are employed, restricted to predefined selected routes. This ensures more efficient management and greater flexibility in the transportation of biomass across the supply chain.

Model Assumptions

- The primary biomass resources consist of Paulownia trees and forest residues.
- The initial locations of farms, preprocessing centers, and biogas facilities are predetermined.
- Drying units are installed at farms if crops are harvested from those farms.
- Drying units are installed at warehouses if the warehouses are operational.
- Energy demand and biomass supply are considered stochastic variables.

- The fixed costs of facility construction are modeled as uncertain and fuzzy parameters.
- Two types of warehouses (rental and constructible) with varying capacities are considered, depending on the harvested volume and available budget.
- Preprocessing centers are designed with three different capacity levels.
- The capacity of biogas facilities is assumed to be fixed.
- The transportation system consists of two vehicle types (trucks and trailers) operating along predefined routes.
- The water required for facilities and the water and fertilizers required for farms are estimated, and recycled water production is adjusted accordingly.
- In the proposed model, decisions regarding warehouse selection (construction or rental), the location of preprocessing centers and biogas facilities, the assignment of different capacity levels to these facilities, and the installation of water pipelines are all incorporated as part of the model development.

The impacts of uncertain supply and demand are examined among the various aspects of uncertainty in the biofuel supply chain. To this end, the supply data are adjusted using uniform percentage variations (increases or decreases) to evaluate the model's performance under different fluctuation conditions. For solving the multi-objective model, the ε-constraint method is employed, which, by generating a set of Pareto-optimal solutions, enables the provision of optimal and sustainable decisions under uncertainty. This method effectively balances conflicting objectives, including environmental and economic goals, and facilitates the selection of optimal decision-making pathways for policymakers (Duc et al., 2021).

Furthermore, the fixed costs of establishing facilities such as warehouses, preprocessing centers, and refineries are modeled using fuzzy logic to more realistically consider the actual fluctuations associated with investment and operational costs. For these costs, three levels are defined: minimum (representing optimistic conditions), most likely (representing normal conditions), and maximum (representing pessimistic conditions).

Integrating the fuzzy approach with the ε-constraint method allows evaluating model performance under different conditions, including optimistic and pessimistic scenarios. This integration allows decision-makers to examine the effect of changes in investment costs on various objectives, including reducing total costs, minimizing unmet demand, and reducing greenhouse gas emissions. Finally, sensitivity analysis is carried out by considering different parameters to demonstrate the vital role of the model in establishing a balance between conflicting objectives and to validate the robustness of the model results under uncertainty.

Mathematical Modeling

The proposed model is a Mixed-Integer Linear Programming (MILP) model, the components of which are introduced as follows:

Sets	
Notation	Description
a	Set of wastewater sources
h	Set of wastewater treatment plants and effluent lagoons
i	Set of harvested farmlands (wood biomass and Paulownia trees)
p	Set of harvested product types (wood biomass or Paulownia trees)
j	Set of buildable warehouses
j'	Set of rental warehouses
k	Set of preprocessing centers
k'	Set of capacity levels for preprocessing centers
m	Biomass moisture percentage level
r	Set of biogas facilities
d	Set of demand centers
A_1	Set of selected transportation routes from farms to buildable or rental warehouses
A_2	Set of selected transportation routes from warehouses to preprocessing centers
A_3	Set of selected transportation routes from preprocessing centers to biogas facilities
A_4	Set of selected transportation routes from biogas facilities to demand centers
Economic Parameters	
Notation	Description
$\widetilde{\mathrm{fcws1}}$	Fixed cost of constructing a buildable warehouse j_1 (fuzzy)
$\widetilde{\mathrm{fcws2}}$	Fixed cost of renting warehouse j_2 (fuzzy)
$\widetilde{\mathrm{fcwc}}_{kk'}$	Fixed cost of establishing preprocessing center k with capacity level K' (fuzzy)
$\widetilde{\mathrm{fcBG}}$	Fixed cost of establishing a biogas facility (fuzzy)
$\widetilde{cv}$	Biomass purchase cost (fuzzy)
$\widetilde{\mathrm{fcdrs}}$	Fixed cost of installing a drying device on the farm (fuzzy)
$\widetilde{\mathrm{fcdrws}}$	Fixed cost of installing a drying device in warehouses (fuzzy)
$\widetilde{\mathrm{fctru1}}$	Fixed cost of truck rental for biomass transport to warehouses and preprocessing centers (fuzzy)
$\widetilde{\mathrm{fctru2}}$	Fixed cost of tank trailer (truck) rental for transporting processed biomass and biogas (fuzzy)
ct	Fuel cost for transportation
cvw	Labor cost for collecting biomass type p from farm i
$cvwc$	Labor cost for employees at the preprocessing centers
$cvBG$	Labor cost for employees at biogas facilities
$cvws$	Labor cost for storage and drying of biomass
CRF_{hi}	Transportation cost of fertilizer from treatment center h to farm i
CRW_{ah}	Transportation cost of sludge and effluent from the wastewater source a to the treatment center h
$FCPA_{hk}$	Construction cost of water pipeline between treatment center h and preprocessing center k
$FCPB_{hr}$	Construction cost of water pipeline between treatment center h and biogas facility r
$FCPJ_{hi}$	Construction cost of water pipeline between treatment center h and farm i
CTJ	Wastewater treatment cost for supplying irrigation water to farms (per cubic meter)
CTA	Wastewater treatment cost for supplying operational water to preprocessing centers (per cubic meter)
CTB	Wastewater treatment cost for supplying operational water to biogas facilities (per cubic meter)
CTF	Cost of wastewater separation and conversion to fertilizer for farm use (per cubic meter)
Environmental Parameters	
Notation	Description

EWS	Greenhouse gas emissions from warehouse construction per square meter of warehouse space
$EWC1$	Greenhouse gas emissions from the preprocessing center construction per square meter of center space
$EWC2$	Greenhouse gas emissions from processing each ton of biomass in the preprocessing centers
$EBG1$	Greenhouse gas emissions from biogas facility construction per square meter of facility space
$EBG2$	Greenhouse gas emissions from the entry of each ton of biomass into biogas facilities
ept	CO_2 emission factor for transportation by truck (grams per kilometer)
ett	CO_2 emission factor for transportation by tank trailer (grams per kilometer)
EJP_{hi}	Greenhouse gas emissions from constructing a pipeline between treatment center h and farm i per meter of pipe
EAP_{hk}	Greenhouse gas emissions from constructing a pipeline between treatment center h and preprocessing center k per meter of pipe
EBP_{hk}	Greenhouse gas emissions from constructing a pipeline between the treatment center h and the biogas facility r per meter of pipe
ETF	Greenhouse gas emissions from transporting 1 ton of produced fertilizer
ESW	Greenhouse gas emissions from transporting 1 ton of sludge and effluent
Warehouse risk parameters	
Notation	Description
δS	Standard deviation of storage capacity in the warehouse
wr	Waste and damage rate of goods in the warehouse
Dt	Delivery delay is considered a risk factor
SI	Warehouse safety index, whose inverse is considered a safety risk
α	Storage cost coefficient of biomass in the warehouse
β	Waste risk coefficient in the warehouse
γ	Insurance cost risk coefficient for biomass in the warehouse
δ	Delivery delay coefficient for biomass in the warehouse
θ	Safety index coefficient for biomass in the warehouse
Technical Parameters	
Notation	Description
$capws1_{j_1}$	Capacity of buildable warehouse j_1
$capws2_{j_2}$	Capacity of rental warehouse j_2
$capwc_{kk'}$	Capacity of preprocessing center k at level k'
$capBG_r$	Capacity of biogas refinery r
$captru1$	Truck transport capacity
$captru2$	Tank trailer (truck) transport capacity
f^{pt}	Fuel consumption rate for truck transportation (km per liter)
f^{tt}	Fuel consumption rate for tank trailer transportation (km per liter)
cr^{W-BG}	Conversion rate from biomass to biogas (cubic meters per ton)
cr^{mk}	Conversion factor in megawatts
cr^{BG-E}	Conversion rate from biogas to electricity (cubic meters per ton)
d^{min}	Minimum agreement on electricity produced for the community (percentage)
q^1	Minimum capacity (5 MW) for biogas facility
q^2	Minimum capacity (6 MW) for biogas facility
q^3	Minimum capacity (7 MW) for biogas facility
q^4	Minimum capacity (8 MW) for biogas facility
q^5	Minimum capacity (9 MW) for biogas facility
M	A sufficiently large number (Big-M)
MWM_i	Maximum amount of wood biomass in farm i
$dws1_{ij_1pA_1}$	Distance of route A1 from farm i to buildable warehouse j_1
$dws2_{ij_2pA_1}$	Distance of route A1 from farm i to rental warehouse j_2

$dwc1_{j_1kpA_2}$	Distance of route A2 from buildable warehouse j_1 to preprocessing center k
$dwc2_{j_2kpA_2}$	Distance of route A2 from rental warehouse j_2 to preprocessing center k
dBG_{krA_3}	Distance of route A3 from preprocessing center k to biogas facility r
MSW_a	Maximum level of sludge and effluent available at wastewater source a
$CAPTRET_h$	Maximum acceptable capacity of sludge and effluent at treatment center h
$PIPMJ_{hi}$	Maximum pipeline capacity for irrigation water transfer from treatment center h to farm i
$PIPMA_{hk}$	Maximum pipeline capacity for operational water transfer from treatment center h to preprocessing center k
$PIPMB_{hr}$	Maximum pipeline capacity for operational water transfer from treatment center h to biogas facility r
FF_i	Amount of fertilizer required for planting Paulownia trees in farm i
WBW_i	Amount of water required for cultivating Paulownia trees in farm i
WBC_k	Amount of water required for biomass processing in preprocessing center k
WBG_r	Amount of water required for biomass-to-biogas conversion in biogas facility r
$\gamma 2$	Conversion factor from sludge and effluent to fertilizer (tons)
$\beta 2$	Conversion factor from sludge and effluent to treated water (cubic meters per ton)
φ	Paulownia tree growth factor with sufficient water and fertilizer supply
Random variables	
Notation	Description
S_{ip}	Amount of biomass type p supplied from farm i
d_d	Electricity demand for each demand center d
Continuous decision variables	
Notation	Description
L_{ipm}	Total amount of biomass type p purchased from farm i with moisture level m
$inv1_{j_1pm}$	Amount of biomass type p stored in buildable warehouse j_1 with moisture level m
$inv2_{j_1pm}$	Amount of biomass type p stored in rental warehouse j_2 with moisture level m
$dinv1_{j_1pmm'}$	Amount of biomass type p dried in buildable warehouse j_1, from moisture level m to m′ (secondary moisture reduction in warehouse)
$dinv2_{j_2pmm'}$	Amount of biomass type p dried in rental warehouse j_2, from moisture level m to m′ (secondary moisture reduction in warehouse)
M_k	Amount of biomass processed in the preprocessing center k
N_r	Amount of wood chips used in the biogas facility r
B_d	Amount of biogas produced for the demand center d
E_d	Amount of electricity produced for the demand center d
YBG_r	Decision variable for establishing a biogas facility r
$Xws1_{ij_1pmA_1}$	Flow/quantity of biomass type p with moisture level m from farm i to buildable warehouse j_1 via selected route A1
$Xws2_{ij_2pmA_1}$	Flow/quantity of biomass type p with moisture level m from farm i to rental warehouse j_2 via selected route A1
$Xwc1_{j_1kpmA_2}$	Flow/quantity of biomass type p with moisture level m from buildable warehouse j_1 to preprocessing center k via selected route A2
$Xwc2_{j_2kpmA_2}$	Flow/quantity of biomass type p with moisture level m from rental warehouse j_2 to preprocessing center k via selected route A2
XBG_{krA_3}	Flow/quantity of processed biomass from preprocessing center k to biogas facility r via selected route A3
XD_{drA_4}	Flow/quantity of electricity produced for the demand center d from the biogas facility r via selected route A4
Ud_d	Amount of unmet electricity demand for the demand center d
SW_{ah}	Flow/quantity of sludge and effluent from wastewater source a to treatment center h
TJ_{hi}	Flow/quantity of treated water from treatment center h to farm i

TA_{hk}	Flow/quantity of treated water from treatment center h to preprocessing center k
TB_{hr}	Flow/quantity of treated water from treatment center h to biogas facility r
TF_{hi}	Flow/quantity of produced fertilizer from treatment center h to farm i
Binary decision variables	
Notation	Description
drs_i	Installing a drying machine on the farm i
$drws1_{j1}$	Installing a drying machine in the constructed warehouse j1
$drws2_{j2}$	Installing a dryer in a rented warehousej_2
$Yws1_{j_1}$	Setting up a buildable warehousej1
$Yws2_{j_2}$	Use of rented warehouse j_2
$Ywc_{kk'}$	Installing a preprocessing center k with capacity k'
$trusw1_{ij1A1}$	Using a truck to transport biomass from farm i to the constructed warehouse j1 via the selected route A_1
$trusw2_{ij2A1}$	Using a truck to transport biomass from farm i to rental warehouse j2 via the selected route A_2
$truwc1_{j1kA2}$	Using a truck to transport biomass from the constructed warehouse j1 to the pre-processing center k via the selected route A_2
$truwc2_{j2kA2}$	Using a truck to transport biomass from rental warehouse j_2 to pre-processing center k via selected route A_2
$truBG_{krA3}$	Using a tank truck to transport the processed biomass from the pre-processing center k to the biogas facility r via the selected route A_3
$trud_{rdA4}$	Using a tank truck to transport biogas produced from biogas facilities r to applicants d via the selected route A_4
$Wws1_{ij_1pmA_1}$	Transport of biomass type p with moisture percentage m from farm i to constructed warehouse j1 via selected route A_1
$Wws2_{ij_2pmA_1}$	Transport of biomass type p with moisture percentage m from farm i to rental warehouse j_2 via selected route A_1
$Wwc1_{j_1kpmA_2}$	Transfer of biomass type p with moisture percentage m from the constructed warehouse j1 to the pre-processing center k via the selected route A_2
$Wwc2_{j_2kpmA_2}$	Transport of biomass type p with moisture percentage m from rental warehouse j2 to pre-processing center k via selected route A_2
WBG_{krA_3}	Binary variable equal to 1 if processed biomass is transported from preprocessing center *k* to biogas facility *r* via selected route A3; 0 otherwise
Q_r^1	Binary variable to enforce the minimum installed capacity (5 MW) for a biogas facility
Q_r^2	Binary variable to enforce the minimum installed capacity (6 MW) for a biogas facility
Q_r^3	Binary variable to enforce the minimum installed capacity (7 MW) for a biogas facility
Q_r^4	Binary variable to enforce the minimum installed capacity (8 MW) for a biogas facility
Q_r^5	Binary variable to enforce the minimum installed capacity (9 MW) for a biogas facility
WJ_{hi}	Binary variable equal to 1 if the water pipeline from treatment center *h* to farm *i* is used; 0 otherwise
WA_{hk}	Binary variable equal to 1 if the water pipeline from treatment center *h* to preprocessing center *k* is used; 0 otherwise
WB_{hr}	Binary variable equal to 1 if the water pipeline from treatment center *h* to biogas facility *r* is used; 0 otherwise

Model Objective Functions

The proposed model focuses on optimizing four key objectives: cost, environmental impact, social impact, and warehouse-related risk.

Economic Objective Function

The economic objective function encompasses several cost components, including biomass purchase cost (BPC), drying cost (DRC), warehouse operation cost (INC), pre-processing center cost (PCC), biogas facility cost (BFC), water transfer cost (WTC), and transportation cost (TC). This objective can be mathematically represented as shown in Equation (1):

$$\text{Min Z1} = \text{BPC+DRC+INC+TC+WC+PCC+BFC+WTC} \tag{1}$$

The expenses associated with purchasing biomass and the wages of farm workers are outlined in Equation (2).

$$\text{BPC} = \sum_{i}\sum_{\text{p}}\sum_{\text{m}} \widetilde{cv}(L_{ipm}) + \sum_{i}\sum_{\text{p}}\sum_{\text{m}} cvw_{ip}L_{ipm} \tag{2}$$

Equation (3) elucidates the costs related to drying, encompassing both field and warehouse drying operations.

$$\begin{aligned} \text{DRC} = &\sum_{i} \widetilde{\text{fcdrs}}\, drs_i + \widetilde{\text{fcdrws}}.(\sum_{\text{j1}} drws1_{j1} + \sum_{\text{j2}} drws1_{j2}) \\ &+ cvws.(\sum_{\text{j1}}\sum_{p}\sum_{\text{m}}\sum_{m\prime} dinv1_{j_1pmm\prime} + \sum_{\text{j2}}\sum_{p}\sum_{\text{m}}\sum_{m\prime} dinv2_{j_2pmm\prime}) \end{aligned} \tag{3}$$

The warehousing costs, including those associated with constructed or rented facilities, are addressed in Equation (4).

$$\text{INC} = \sum_{\text{j1}} \widetilde{\text{fcws1}}\ \text{Yws1}_{\text{j}_1} + \sum_{\text{j2}} \widetilde{\text{fcws2}}\ \text{Yws2}_{\text{j}_2}) \tag{4}$$

Fixed costs associated with establishing pre-processing centers, biogas facilities, and wages for product preparation are presented in Equations (5) and (6).

$$\text{PCC} = \sum_{\text{k}}\sum_{\text{k}\prime} \widetilde{\text{fcwc}}_{\text{kk}\prime}\ \text{Ywc}_{\text{kk}\prime} + \sum_{\text{k}}\sum_{\text{m}} cvwc\ M_{km} \tag{5}$$

$$\text{TC} = \sum_{\text{r}} \widetilde{\text{fcBG}}_r YBG_r + \sum_{\text{r}} cvBGN_r \tag{6}$$

Equation(7) calculates the costs of water treatment, including transportation to various facilities, as well as the expenses involved in separating and transporting fertilizer to the fields.

$$\begin{aligned} \text{WTC} = &\sum_{h}\sum_{i} CTJ_{hi}TJ_{hi} + \sum_{h}\sum_{k} CTA_{hk}TA_{hk} + \sum_{h}\sum_{r} CTB_{hr}TB_{hr} \\ &+ \sum_{h}\sum_{i} CTF_{hi}TF_{hi} + \sum_{h}\sum_{i} CRF_{hi}TF_{hi} + \sum_{a}\sum_{h} CRW_{ah}SW_{ah} \\ &+ \sum_{h}\sum_{i} FCPJ_{hi}WJ_{hi} + \sum_{h}\sum_{k} FCPA_{hk}WA_{hk} \\ &+ \sum_{h}\sum_{r} FCPB_{hr}WB_{hr} \end{aligned} \tag{7}$$

Equation (8) details the total fixed and variable transportation costs and vehicle expenses across all categories within the network.

$$\begin{aligned}
\mathrm{BFC} = & \sum_{i}\sum_{j_1}\sum_{p}\sum_{m}\sum_{A_1} \mathrm{dws1}_{\mathrm{ij_1pA_1}}\,\mathrm{ct}\,\mathrm{Xws1}_{\mathrm{ij_1pmA_1}}/\mathrm{f}^{\mathrm{pt}} \\
& + \sum_{i}\sum_{j2}\sum_{p}\sum_{m}\sum_{A1} \mathrm{dws2}_{\mathrm{ij_2pA_1}}\,\mathrm{ct}\,\mathrm{Xws2}_{\mathrm{ij_2pmA_1}}/\mathrm{f}^{\mathrm{pt}} \\
& + \sum_{j_1}\sum_{k}\sum_{p}\sum_{m}\sum_{A2} \mathrm{dwc1}_{\mathrm{j_1kpA_2}}\,\mathrm{ct}\,\mathrm{Xwc1}_{\mathrm{j_1kpmA_2}}/\mathrm{f}^{\mathrm{pt}} \\
& + \sum_{j2}\sum_{k}\sum_{p}\sum_{m}\sum_{A2} \mathrm{dwc1}_{\mathrm{j_2kpA_2}}\,\mathrm{ct}\,\mathrm{Xwc2}_{\mathrm{j_2kpmA_2}}/\mathrm{f}^{\mathrm{pt}} \\
& + \sum_{k}\sum_{r}\sum_{A_3} \mathrm{dBG}_{\mathrm{krA_3}}\ \mathrm{ct}\ \ \mathrm{XBG}_{\mathrm{krA_3}}/\mathrm{f}^{\mathrm{tt}} \\
& + \widetilde{\mathrm{fctru1}}\Big(\sum_{i}\sum_{j_1}\sum_{j2}\sum_{k}\sum_{A1}\sum_{A2}(trusw1_{ij1A1} + trusw2_{ij2A1} \\
& + truwc1_{j1kA2} + truwc2_{j2kA2})\Big) \\
& + \widetilde{\mathrm{fctru2}}\Big(\sum_{k}\sum_{r}\sum_{d}\sum_{A3}\sum_{A4} truBG_{krA3} + truBG_{rdA4}\Big)
\end{aligned} \tag{8}$$

Social Objective Function

The second objective function aims to assess the social impacts of the biofuel supply chain network by quantifying the total unmet electricity demand in various demand areas, as represented in Equation 9.

$$\mathrm{Min\ Z2} = \mathrm{M}\sum_{d} \mathrm{Ud_d} \tag{9}$$

Environmental Objective Function

The environmental objective function is designed to measure and minimize carbon dioxide (CO2) emissions associated with facility construction (denoted as EMCF) and transportation activities (denoted as EMWT) throughout different segments of the proposed network.

$$Min\ Z2 = EMCF + EMWT \tag{10}$$

Equation 11 accounts for carbon emissions related to the construction of warehouses, pre-processing centers, biogas facilities, and water exploitation facilities. In contrast, Equation 12 outlines the carbon emissions from transportation activities across the supply chain.

$$\begin{aligned}
& EMCF = EWS\,.\Big(\sum_{\mathrm{j1}} capws1_{j_1}\mathrm{Yws1}_{\mathrm{j_1}} \\
& EBG1\,.\Big(\sum_{\mathrm{r}} capBG_r\, YBG_r\Big) + \sum_{\mathrm{r}} EBG2\, N_r
\end{aligned} \tag{11}$$

$$+\sum_{h}\sum_{i} EJP_{hi}\, WJ_{hi} + \sum_{h}\sum_{k} EAP_{hk}\, WA_{hk}$$
$$+\sum_{h}\sum_{r} EBP_{hr}\, WB_{hr} + \sum_{h}\sum_{i} ETF_{hi}\, TF_{hi}$$
$$+\sum_{a}\sum_{h} ESW_{ah}\, SW_{ah}$$

$$EMWT = \sum_{i}\sum_{j_1}\sum_{p}\sum_{m}\sum_{A_1} dws1_{ij_1pA_1}\; ept\; Wws1_{ij_1pmA_1} + \sum_{i}\sum_{j_2}\sum_{p}\sum_{m}\sum_{A_1} dws2_{ij_2pA_1}\; ept\; Wws2_{ij_2pmA_1} \tag{12}$$
$$+\sum_{j_1}\sum_{k}\sum_{p}\sum_{m}\sum_{A_2} dwc1_{j_1kpA_2}\; ept\; Wwc1_{j_1kpmA_2} + \sum_{j_2}\sum_{k}\sum_{p}\sum_{m}\sum_{A_2} dwc2_{j_2kpA_2}\; ept\; Wwc2_{j_2kpmA_2}$$
$$+\sum_{k}\sum_{r}\sum_{A_3} dBG_{krA_3}\; ett\; WBG_{krA_3}$$

Objective Function for Calculating Warehouse Risk

The fourth objective function, represented by equation (13), aims to minimize warehouse risk. This function incorporates several risk indicators, including the storage conditions of inventories within the warehouse, potential product losses, delays in product delivery, safety issues related to theft, fire hazards, proper ventilation, and other relevant factors. The weighting coefficients (α, β, γ, δ, θ) are used to quantify the relative importance of each variable in the overall assessment of warehouse risk, as determined by specialists and experts in the field**.**

$$Min\ Z4 = \alpha.\delta S\Big(\sum_{j1} \mathrm{Yws1}_{j_1} + \sum_{j2} \mathrm{Yws2}_{j_2}\Big) + \beta.wr\Big(\sum_{j1} \mathrm{Yws1}_{j_1} + \sum_{j2} \mathrm{Yws2}_{j_2}\Big) + \gamma.Ins\Big(\sum_{j1} \mathrm{Yws1}_{j_1} + \sum_{j2} \mathrm{Yws2}_{j_2}\Big) + \delta.Dt\Big(\sum_{j1} \mathrm{Yws1}_{j_1} + \sum_{j2} \mathrm{Yws2}_{j_2}\Big) + \theta.(1-SI)\Big(\sum_{j1} \mathrm{Yws1}_{j_1} + \sum_{j2} \mathrm{Yws2}_{j_2}\Big) \tag{13}$$

Constraints

The model incorporates several types of constraints, including capacity constraints, inventory constraints, technical constraints, and equilibrium constraints, which are defined as follows:

$$\sum_{m} L_{ipm} \le S_{ip} \qquad \forall\, i,p \tag{14}$$

$$\sum_{m} L_{ipm} \le (WBW_i + FF_i)\varphi + MWM \quad \forall\, i,p \tag{15}$$

$$\sum_{i} drs_i \geq (\sum_{p}\sum_{m} L_{ipm})/M \qquad \forall\, i \tag{16}$$

Constraints (14) and (15) ensure that the amount of biomass purchased from each farm does not exceed the available biomass supply and the respective quantities of trees and wood stock on each farm. Constraint (16) stipulates that a drying device must be installed on the farm to reduce the initial moisture content of the biomass.

$$\sum_{j_1}\sum_{A_1} Xws1_{ij_1pmA_1} + \sum_{j_2}\sum_{A_1} Xws2_{ij_2pmA_1} = L_{ipm} \quad \forall\, i,p,m \tag{17}$$

$$\sum_{i}\sum_{p}\sum_{m}\sum_{A_1} Xws1_{ij_1pmA_1} \leq\ capws1_{j_1} Yws1_{j_1} \quad \forall\, j_1 \tag{18}$$

$$\sum_{i}\sum_{p}\sum_{m}\sum_{A_1} Xws2_{ij_2pmA_1} \leq\ capws2_{j_2} Yws2_{j_2} \quad \forall\, j_2 \tag{19}$$

Constraint (17) defines the biomass transported from the farm to the storage facilities. Furthermore, constraints (18) and (19) ensure that the flow of transported biomass from the farm does not exceed the storage capacity limits.

$$drws1_{j1} = Yws1_{j_1} \quad \forall\, j_1 \tag{20}$$

$$drws1_{j2} = Yws1_{j_2} \quad \forall\, j_2 \tag{21}$$

$$inv1_{j_1pm} = \sum_{i}\sum_{A_1} Xws1_{ij_1pmA_1} \quad \forall\, j_1,p,m \tag{22}$$

$$inv2_{j_2pm} = \sum_{i}\sum_{A_1} Xws1_{ij_2pmA_1} \quad \forall\, j_2,p,m \tag{23}$$

$$inv1_{j_1pm} = \sum_{m\prime<m} dinv1_{j_1pmm\prime} \qquad \forall\, j_1,p,m \tag{24}$$

$$inv2_{j_2pm} = \sum_{m\prime<m} dinv2_{j_2pmm\prime} \qquad \forall\, j_2,p,m \tag{25}$$

Constraints (20) and (21) stipulate the installation of dryers in each warehouse. Constraints (22) and (23) define the biomass inventory levels within the warehouses, while constraints (24) and (25) pertain to the inventory after the secondary moisture reduction of the biomass at the warehouse site.

$$(1 - drws1_{j1})inv1_{j_1pm} = dinv1_{j_1pmm\prime} \quad \forall\, j_1,p,m,m' = m \tag{26}$$

$$(1 - drws2_{j2})inv2_{j_2pm} = dinv2_{j_2pmm\prime} \quad \forall\, j_2,p,m,m' = m \tag{27}$$

The above constraints indicate that, in the absence of a drying device installed in warehouses, the inventory will retain its initial moisture content.

$$\sum_{i}\sum_{m}\sum_{A_1} Xws1_{ij_1pmA_1} \geq \sum_{k}\sum_{m}\sum_{A_2} Xwc1_{j_1kpmA_2} \quad \forall\, j_1,p \tag{28}$$

$$\sum_{i}\sum_{m}\sum_{A_1} Xws2_{ij_2pmA_1} \geq \sum_{k}\sum_{m}\sum_{A_2} Xwc2_{j_2kpmA_2} \quad \forall\, j_2, p \tag{29}$$

$$\sum_{j_1}\sum_{p}\sum_{m}\sum_{A_2} Xwc1_{j_1kpmA_2} + \sum_{j_2}\sum_{p}\sum_{m}\sum_{A_2} Xwc2_{j_2kpmA_2} \leq \sum_{k\prime} capwc_{kk\prime}\, Ywc_{kk\prime} \quad \forall\, k \tag{30}$$

Constraint (28) and (29) constitute the model's first equilibrium equation, reflecting the balance of biomass transported from the warehouse to the processing center. Additionally, equation (30) specifies that the total biomass transported must not exceed the capacity of the pre-processing centers.

$$\sum_{k\prime} Ywc_{kk\prime} \leq 1 \quad \forall\, k \tag{31}$$

$$M_k = \sum_{j_1}\sum_{p}\sum_{m}\sum_{A_2} Xwc1_{j_1kpmA_2} + \sum_{j_2}\sum_{p}\sum_{m}\sum_{A_2} Xwc2_{j_2kpmA_2} \quad \forall\, k \tag{32}$$

These two constraints elucidate the number of pre-processing centers required, their respective capacities and the volume of biomass processed.

$$\sum_{j_1}\sum_{p}\sum_{m}\sum_{A_2} Xwc1_{j_1kpmA_2} + \sum_{j_2}\sum_{p}\sum_{m}\sum_{A_2} Xwc2_{j_2kpmA_2} \geq \sum_{r}\sum_{A_3} XBG_{krA_3} \quad \forall\, k \tag{33}$$

$$\sum_{k}\sum_{A_3} XBG_{krA_3} \leq capBG_r YBG_r \quad \forall\, r \tag{34}$$

$$N_r = \sum_{k}\sum_{A_3} XBG_{krA_3} \quad \forall\, r \tag{35}$$

Equation (33) is the second equilibrium equation, establishing a relationship between the total biomass processed and the biogas produced. Equation (34) delineates the capacity constraint of the facility, while constraint (35) quantifies the amount of biogas generated.

$$\sum_{k}\sum_{A_3} XBG_{krA_3} \geq \sum_{d}\sum_{A_4} XD_{rdA_4} \quad \forall\, r \tag{36}$$

Equation (36) represents the third equilibrium equation that describes the relationship between the transport of produced biogas and the corresponding consumption demand.

$$YBG_r = q^1 Q_r^1 + q^2 Q_{\mathrm{r}}^2 + q^3 Q_r^3 + q^4 Q_{\mathrm{r}}^4 + q^5 Q_{\mathrm{rt}}^5 \quad \forall\, r \tag{37}$$

$$YBG_r \leq 1 \quad \forall\, r \tag{38}$$

$$B_d = cr^{W-BG} \sum_{r}\sum_{A_4} Xd_{rdA_4} \quad \forall\, d \tag{39}$$

$$E_d = cr^{mk} cr^{BG-E} B_d \quad \forall\, d \tag{40}$$

Constraint (37) addresses only a single capacity, even though each biogas facility is designed with five distinct capacities. Constraint (38) facilitates the selection of a biogas facility based on the specified capacity requirements. Constraints (39) and (40) quantify the amounts of biogas and electricity produced, respectively.

$$E_d \geq d^{min} d_d \quad \forall\, d \tag{41}$$
$$Ud_d = d_d - E_d \quad \forall\, d \tag{42}$$
$$M(Wws1_{ij_1pmA_1}) \geq Xws1_{ij_1pmA_1} \quad \forall\, i, j_1, p, m, A_1 \tag{43}$$
$$M(Wws2_{ij_2pmA_1}) \geq Xws2_{ij_2pmA_1} \quad \forall\, i, j_2, p, m, A_1 \tag{44}$$
$$M(Wwc_{1j_1kpmA_2}) \geq Xwc1_{j_1kpmA_2} \quad \forall\, j_1, k, p, m, A_2 \tag{45}$$
$$M(Wwc2_{j_2kpmA_2}) \geq Xwc2_{j_2kpmA_2} \quad \forall\, j_2, k, p, m, A_2 \tag{46}$$
$$M(WBG_{krA_3}) \geq XBG_{krA_3} \quad \forall\, k, r, A_3 \tag{47}$$

Constraint (41) indicates that the electricity generated exceeds consumption demand by a specified percentage. Constraint (42) quantifies the extent of unmet electricity demand. Additionally, Constraints (43) through (47) assess the reliability of the chosen routes for transporting products from farms to warehouses, pre-processing centers, and biogas facilities, considering these factors in an effort to mitigate environmental impacts.

$$\sum_h SW_{ah} \leq MSW_a \quad \forall\, a \tag{48}$$
$$\sum_h SW_{ah} \leq CAPTRET_a \quad \forall\, a \tag{49}$$
$$TJ_{hi} \leq PIPMJ_{hi}\, WJ_{hi} \quad \forall\, h, i \tag{50}$$
$$TA_{hk} \leq PIPMA_{hk}\ WJ_{hk} \quad \forall\, h, k \tag{51}$$
$$TB_{hr} \leq PIPMB_{hr}\ WJ_{hr} \quad \forall\, h, r \tag{52}$$
$$\sum_a SW_{ah}\, \gamma 2 = \sum_i TF_{hi} \quad \forall\, h \tag{53}$$
$$\sum_a SW_{ah}\, \beta 2 = \sum_i TJ_{hi} + \sum_k TA_{hk} + \sum_r TB_{hr} \quad \forall\, h \tag{54}$$
$$\sum_h TF_{hi} \geq FF_i \quad \forall\, i \tag{55}$$
$$\sum_h TJ_{hi} \geq WBW_i \quad \forall\, i \tag{56}$$
$$\sum_h TA_{hk} \geq WBC_k \quad \forall\, k \tag{57}$$
$$\sum_h TB_{hr} \geq WBG_r \quad \forall\, r \tag{58}$$

Constraints (48) to (58) are incorporated to facilitate effective water resource management. Specifically, constraints (48) and (49) stipulate that the flow of sludge and effluent must not exceed the wastewater treatment capacity and the maximum acceptable limits at the treatment plant. Constraints (50) to (52) address the volume of treated water, ensuring that it remains within the capacity of the water transfer pipelines connecting the treatment plants to the farms, pre-processing centers, and biogas plants.

Furthermore, constraints (53) and (54) quantify the amount of fertilizer produced and the volume of treated water transported. Constraint (55) establishes that the volume of fertilizer generated must exceed the requirements of the farms, while constraints (56) to (58) ensure that the amount of treated water meets or exceeds the required capacities for the farms, pre-processing centers, and biogas facilities.

$$\sum_p \sum_m Xws1_{ij_1pmA_1} \leq Captruw1 * trusw1_{ij1A1} \qquad \forall\, i, j_1, A_1 \tag{59}$$

$$\sum_p \sum_m Xws2_{ij_2pmA_1} \leq Captruw1 * trusw2_{ij2A1} \qquad \forall\, i, j_2, A_1 \tag{60}$$

$$\sum_p \sum_m Xwc1_{j_1mpA_2} \leq Captruw1 * truwc1_{j1kA2} \qquad \forall\, j_1, k, A2 \tag{61}$$

$$\sum_p \sum_m Xwc2_{j_2mpA_2} \leq Captruw1 * truwc2_{j2kA2} \qquad \forall\, j_2, k, A2 \tag{62}$$

$$XBG_{krA_3} \leq captru2 * truBG_{krA_3} \qquad \forall\, k, r, A_3 \tag{63}$$

$$XD_{rdA_4} \leq captru2 * trud_{rdA_4} \qquad \forall\, r, d, A_4 \tag{64}$$

The constraints presented above delineate the vehicle requirements at various levels within the network. Specifically, constraints (59) and (62) define the capacity limits of trucks transporting products from the farms to the warehouses and subsequently from the warehouses to the pre-processing centers. Additionally, constraints (63) and (64) specify the trailer capacity constraints involved in transporting processed biomass to the biogas plant and, subsequently, from the biogas plant to the demand centers.

$$\begin{aligned} &drs_i, drws1_{j1}, drws2_{j2}, Yws1_{j_1}, Yws2_{j_2}, Ywc_{kk'}, Wws1_{ij_1pmA_1}, Wws2_{ij_2pmA_1}, Wwc1_{j_1kpmA_2},\\ &Wwc2_{j_2kpmA_2}, WBG_{krA_3}, Q_r^1, Q_r^2, Q_r^3, Q_r^4, Q_r^5 \in \{0,1\} \end{aligned} \tag{65}$$

$$YBG_r, Xws1_{ij_1pmA_1}, Xws2_{ij_2pmA_1}, Xwc1_{j_1kpmA_2}, Xwc2_{j_2kpmA_2}, XBG_{krA_3} \geq 0 \tag{66}$$

$$\begin{aligned} &YBG_r, L_{ipm}, inv1_{j_1pm}, inv2_{j_1pm}, dinv1_{j_1pmm'},\\ &dinv2_{j_2pmm'}, , M_k, N_r, B_d, E_d, Ud_d, SW_{ah}, TJ_{hi}, TA_{hk}, TB_{hr}, TF_{hi} \geq 0 \end{aligned} \tag{67}$$

Mathematical Modeling

It is noteworthy that the proposed model includes four objective functions (minimization of total costs, reduction of environmental impacts, improvement of social indicators, and reduction of warehouse risk). The model also comprises a total of 64 constraints. In addition, there are 49 decision variables in total, including 22 continuous variables related to material flows and allocations, 25 binary variables associated with facility selection, routing, and capacity, and 2 stochastic variables corresponding to uncertainty in supply and demand.

To strengthen the theoretical foundation and enhance comparability, the proposed objective functions and constraints are aligned with and supported by recent studies. More specifically, the economic objective (cost minimization) is consistent with recent research on fuzzy multi-objective resilient supply chain models (Nozari et al., 2025). The environmental dimensions are supported by recent studies on sustainable supply chain design (Flores-Siguenza, 2025). The social indicators are validated by up-to-date studies in the field of sustainable agricultural supply chains (Rahbari et al., 2023). Finally, warehouse risk is reinforced and substantiated by recent findings on multi-level food supply chain optimization (Kiani Mavi, 2025).

Linearization of the Model

Equations (26) and (27) exhibit nonlinearity due to the interaction between a binary variable and a continuous variable. To transform these equations into linear form, we introduced the following auxiliary variables, along with accompanying constraints to ensure that these auxiliary variables are restricted to integer values.

Nonlinear constraint	**Variable change**
$(1 - drws1_{j_1})inv1_{j_1pm} = dinv1_{j_1pmm'} \quad \forall\, j_1, p, m, m' = m$	$inv1_{j_1pm} = u_{j_1pmm'}$
Constraints added to the model:	
$u_{j_1pmm'} \geq\ dinv1_{j_1pmm'} - M(1 - drws1_{j_1})$	(68)
$u_{j_1pmm'} \leq\ M\, drws1_{j_1}$	(69)
Nonlinear constraint	**Variable change**
$(1 - drws2_{j_2})inv2_{j_2pm} = dinv2_{j_2pmm'} \quad \forall\, j_2, p, m, m' = m$	$inv2_{j_2pm} = u'_{j_2pmm'}$
Constraints added to the model:	
$u'_{j_2pmm'} \geq\ dinv2_{j_2pmm'} - M(1 - drws2_{j_2})$	(70)
$u'_{j_2pmm'} \leq\ M\, drws2_{j_2}$	(71)

Model Adjustment Utilizing Fuzzy Relations

Fuzzy logic has been employed to model the uncertainty associated with costs. In real-world scenarios, data is often characterized by inaccuracies and instabilities; consequently, these variables have been incorporated into the model as fuzzy numbers to enhance the realism of the analyses. Specifically, startup costs and supply and demand values have been represented as fuzzy numbers. To effectively manage these fuzzy parameters, the methodology proposed by Jimenez et al. (2007) is utilized. This approach is designed to transform the fuzzy mixed-integer linear optimization model (FMILP) into an equivalent deterministic model. In this framework, if the fuzzy numbers are defined as triangular (as depicted in Figure 3), and ($\tilde{c} = \{L, M, U\}$) denotes a fuzzy number, then equation (72) can be articulated as follows:

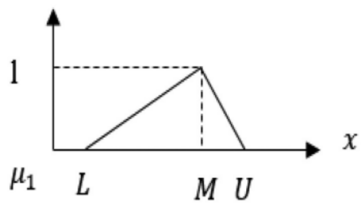


Figure 3. Membership functions of a triangular fuzzy number

$$\begin{cases} f_c(x) = \dfrac{x-L}{M-L} & if \quad L \le x \le M \\ 1 & if \quad x = M \\ g_c(x) = \dfrac{U-x}{U-M} & if \quad L \le x \le M \\ 0 & if \quad x \le M \quad or \quad x \ge U \end{cases} \tag{72}$$

The equations have been formulated to effectively manage fuzzy parameters, allowing for the determination of Pareto frontiers for various objectives. Following the framework proposed by Jimenez (1996), we can interpret relations (73) and (74) such that the interval (EI) and the expected value (EV) are equivalent to ($\tilde{C}$).

$$EI(\widetilde{C}) = [E_1^c, E_2^c] = \left[\int_0^1 f_c^{-1}(x)dx, \int_0^1 g_c^{-1}(x)dx\right] = \left[\frac{L+M}{2}, \frac{M+U}{2}\right] \tag{73}$$

$$EV(\widetilde{C}) = \frac{E_1^c - E_2^c}{2} = \frac{L+2M+U}{4} \tag{74}$$

Utilizing the fuzzy number ranking method established by Jimenez et al. (2007), we can examine relation (75) within the context of a binary set of fuzzy numbers, specifically $\tilde{a}$ and $\tilde{b}$, where the level of $\tilde{b}$ is less than that of $\tilde{a}$.

$$\mu_M(\tilde{a}, \tilde{b}) = \begin{cases} 1 & if \quad E_1^a - E_2^b > 0 \\ \dfrac{E_2^a - E_1^b}{E_2^a - E_1^b - (E_1^a - E_2^b)} & if \quad 0 \in [E_1^a - E_2^b, E_2^a - E_1^b] \\ 0 & if \quad E_1^a - E_2^b < 0 \end{cases} \tag{75}$$

When $\mu_M(\tilde{a}, \tilde{b}) \le \alpha$, it indicates that $\tilde{a}$ is less than or equal to $\tilde{b}$ and the fuzzy constraints in the research model are transformed into the form of equation (76)

$$\tilde{a}x \le \tilde{b}, x \ge 0 \tag{76}$$

According to the above fuzzy relations, relations (2) to (6) in the first objective function will change to relations (77) to (82)

$$BPC = \sum_i \sum_p \sum_m \frac{Lcv + 2Mcv + Ucv}{4}(L_{ipm}) + \sum_i \sum_p \sum_m cvw_{ip} L_{ipm} \tag{77}$$

$$\begin{aligned} \mathrm{DRC} = & \sum_i \frac{Lfcdrs + 2Mfcdrs + Ufcdrs}{4}\, drs_i \\ & + \frac{Lfcdrws + 2Mfcdrws + Ufcdrws}{4}.(\sum_{j1} drws1_{j_1} + \sum_{j2} drws1_{j2}) \\ & + cvws.(\sum_{j1}\sum_p\sum_m\sum_{m\prime} dinv1_{j_1pmm\prime} + \sum_{j2}\sum_p\sum_m\sum_{m\prime} dinv2_{j_2pmm\prime}) \end{aligned} \tag{78}$$

$$\mathrm{INC} = (\sum_{\mathrm{j1}} \frac{Lfcws1 + 2Mfcws1 + Ufcws1}{4} \mathrm{Yws1}_{\mathrm{j}_1} + \sum_{\mathrm{j2}} \frac{Lfcws2 + 2Mfcws2 + Ufcws2}{4} \mathrm{Yws2}_{\mathrm{j}_2}) \tag{79}$$

$$\mathrm{PCC} = \sum_{\mathrm{k}} \sum_{\mathrm{k'}} \frac{Lfcwc_{kk'} + 2Mfcwc_{kk'} + Ufcwc_{kk'}}{4} \mathrm{Ywc}_{\mathrm{kk'}} + \sum_{\mathrm{k}} \sum_{\mathrm{m}} cvwc\ M_{km} \tag{80}$$

$$\mathrm{TC} = \sum_{\mathrm{r}} \frac{LfcBG_r + 2MfcBG_r + UfcBG_r}{4} (YBG_r) + \sum_{\mathrm{r}} cvBGN_r \tag{81}$$

$$\begin{aligned}
\mathrm{BFC} = & \sum_{\mathrm{i}} \sum_{\mathrm{j}_1} \sum_{\mathrm{p}} \sum_{m} \sum_{\mathrm{A}_1} \mathrm{dws1}_{\mathrm{ij_1pA_1}} \mathrm{ct\ Xws1}_{\mathrm{ij_1pmA_1}} / \mathrm{f}^{\mathrm{pt}} \\
& + \sum_{\mathrm{i}} \sum_{\mathrm{j2}} \sum_{\mathrm{p}} \sum_{\mathrm{m}} \sum_{A1} \mathrm{dws2}_{\mathrm{ij_2pA_1}} \mathrm{ct\ Xws2}_{\mathrm{ij_2pmA_1}} / \mathrm{f}^{\mathrm{pt}} \\
& + \sum_{\mathrm{j}_1} \sum_{\mathrm{k}} \sum_{\mathrm{p}} \sum_{\mathrm{m}} \sum_{A2} \mathrm{dwc1}_{\mathrm{j_1kpA_2}} \mathrm{ct\ Xwc1}_{\mathrm{j_1kpmA_2}} / \mathrm{f}^{\mathrm{pt}} \\
& + \sum_{\mathrm{j2}} \sum_{\mathrm{k}} \sum_{\mathrm{p}} \sum_{\mathrm{m}} \sum_{A2} \mathrm{dwc1}_{\mathrm{j_2kpA_2}} \mathrm{ct\ Xwc2}_{\mathrm{j_2kpmA_2}} / \mathrm{f}^{\mathrm{pt}} \\
& + \sum_{\mathrm{k}} \sum_{\mathrm{r}} \sum_{\mathrm{A}_3} \mathrm{dBG}_{\mathrm{krA_3}}\ \mathrm{ct\ XBG}_{\mathrm{krA_3}} / \mathrm{f}^{\mathrm{tt}} \\
& + \frac{Lfctru1 + 2M\mathrm{fct}ru1 + U\mathrm{fct}ru1}{4} (\sum_{\mathrm{i}} \sum_{\mathrm{j}_1} \sum_{\mathrm{j2}} \sum_{k} \sum_{A1} \sum_{A2} (trusw1_{ij1A1} \\
& + trusw2_{ij2A1} + truwc1_{j1kA2} + truwc2_{j2kA2})) \\
& + \frac{Lfctru2 + 2M\mathrm{fct}ru2 + U\mathrm{fct}ru2}{4} (\sum_{k} \sum_{r} \sum_{d} \sum_{A3} \sum_{A4} truBG_{krA3} + trud_{rdA4})
\end{aligned} \tag{82}$$

Given the multi-objective nature of the model, the epsilon constraint method has been employed for its resolution. In this approach, at each stage, one objective function is designated as the primary objective, while the remaining functions are treated as constraints with specified epsilon values to facilitate balance and optimization (Mavrotas, 2009). Equation (83) illustrates the epsilon constraint method.

$$\begin{aligned}
& min\ f_1(x) \\
& \text{subject to} \\
& f_1(x) \leq \varepsilon_2 \\
& f_1(x) \leq \varepsilon_3 \\
& \dots \\
& f_p(x) \leq \varepsilon_p \\
& x \in S
\end{aligned} \tag{83}$$

Results

The model implementation results include an analysis of its performance in achieving various objectives, such as cost reduction, improvement of environmental efficiency, mitigation of social impact, and reduction of inventory risk. Additionally, a sensitivity assessment of the model was performed, considering key parameters such as stochastic supply and demand, fuzzy cost estimates, and fluctuations in raw material prices.

Initial values for these parameters were derived from data and findings from prior research conducted by Ransikarbum and Pitakaso (2024). Relevant assumptions are summarized in Table 2.

Table 2. Assumptions and values of some model parameters

Parameters	Assumptions, values, and explanations
S_{ip}	Five farms are assumed to harvest woody biomass and Paulownia trees. In the first period, it is assumed that approximately 30 tons of biomass can be harvested from each farm.
d_d	Five demand centers are considered for the electricity produced, with an initial demand of approximately 40 MW in the first period.
$Yws1_{j_1}$	It is assumed that three buildable warehouses have capacities of 15 tons.
$Yws2_{j_2}$	It is assumed that there are five rental warehouses with capacities of 10 tons.
$Ywc_{kk'}$	It is assumed that there are five pre-processing centers, each with three different capacity levels of 40, 60, and 80 tons.
YBG_r	It is assumed that five biogas facilities have capacities of 5, 6, 7, 8, and 9 megawatts.
$\widetilde{\mathrm{fcws1}}$	The fixed cost of establishing each buildable warehouse is approximately 300,000 dollars.
$\widetilde{\mathrm{fcws2}}$	The fixed cost for the one-year rental of each rental warehouse is approximately 11,000 dollars.
$\widetilde{\mathrm{fcwc}_{kk'}}$	The fixed cost of establishing each pre-processing center, according to capacity, is approximately 400,000, 600,000, and 800,000 dollars, respectively.
$\widetilde{\mathrm{fcBG}}$	The fixed cost of establishing each biogas facility, according to capacity, is approximately 1,000,000; 1,100,000; 1,200,000; 1,400,000; and 1,500,000 dollars, respectively.
$\widetilde{cv}$	The cost of purchasing each ton of biomass is approximately 1,200 dollars.
cvw	The labor cost for collecting each ton of biomass is 130 dollars.
ct	The fuel cost for transportation is 5 dollars.
f^{pt}	The fuel consumption for the truck is 0.6 liters per kilometer.
f^{tt}	The fuel consumption for transportation by tank trailer is 0.4 liters per kilometer.
ept	The CO2 emission factor for transportation by truck is 0.0006 grams per kilometer.
ett	The CO2 emission factor for transportation by tank trailer is 0.0023 grams per kilometer.

In the proposed method, the model was implemented using GAMS software version 24.8, and Pareto points were obtained by optimizing each objective function individually. The resultant data is presented in Table 3.

Table 3. Optimal values of objective functions

Z4	Z3	Z2	Z1
Reduction of total supply chain (thousand USD)	Reduction of unmet demand (kWh)	Reduction of carbon emissions (kg CO_2)	Reduction of warehouse risk (%)
2850.242	489600	40843	2.615

To establish a set of Pareto points, this set was generated by designating one objective function as the primary objective while treating the others as secondary objectives. This involved applying three different constraint levels for each objective, as detailed in Table 4. The primary aim was to identify optimal combinations of the objective functions, which were presented using the epsilon-constraint method. Consequently, the Pareto frontier was delineated, allowing decision-makers to select the most appropriate option for multi-objective optimization while comprehending the associated trade-offs. Figure 4 illustrates the three-dimensional Pareto diagram, showing the frontier and Pareto values for each objective.

Table 4. Pareto optimal combinations of points for objective functions

Row	Z1	Z2	Z3	Z4	Row	Z1	Z2	Z3	Z4
1	2850.242	1134000	40844.316	3.138	13	3320.682	919200	41058.504	3.661
2	2850.242	1134000	40844.308	3.138	14	3396.552	1134000	40844.453	2.615
3	2850.273	1134000	40844.28	3.138	15	3396.552	1134000	40844.59	2.615
4	2850.275	1134000	40844.288	3.138	16	3426.444	811800	40844.603	3.661
5	2850.284	1134000	40844.29	3.138	17	3426.49	811800	40844.651	3.661
6	3213.688	1026600	40844.408	3.138	18	3426.563	811800	40844.552	3.661
7	3213.688	1026600	40844.376	3.138	19	3577.243	919200	40844.491	3.138
8	3213.688	1026600	40844.376	3.138	20	3577.252	919200	41058.504	3.138
9	3213.688	1026600	40844.438	3.138	21	4095.483	704400	40844.426	3.661
10	3213.763	1026600	40844.414	3.138	22	4095.51	704400	40844.52	3.661
11	3320.682	919200	40844.411	3.661	23	4227.49	597000	40844.489	4.184
12	3320.682	919200	40844.442	3.661	24	4330.729	489600	40844.751	4.184

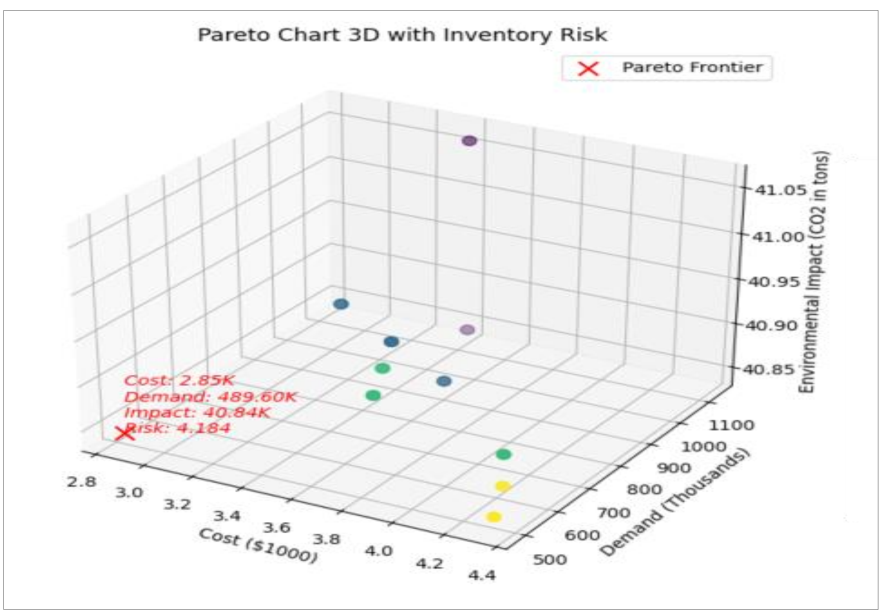


Figure 4. Three-dimensional Pareto frontier analysis for objective function optimization

The illustrated three-dimensional Pareto diagram presents the optimal solutions derived from the biofuel supply chain model with four objectives. This model aims to minimize total supply chain costs (Z4), unmet demand (Z3), carbon emissions (Z2), and warehouse risk (Z1). The Pareto points represent trade-offs among these conflicting objectives, highlighting that improvements in one objective often come at the expense of others. The Pareto frontier delineates the set of efficient solutions, serving as a valuable decision-making tool in supply chain design. A specific point highlighted on the diagram, with a total cost of \$$2.85 \times 10^3$, unmet demand of 4.896×10^5 kWh, CO_2 emissions of 4.084×10^4 kg, and inventory risk of 2.615%, exemplifies an optimal balance among these objectives. Analyzing this diagram enables decision-makers to simultaneously address sustainability and operational challenges within the supply chain.

Considering the stochastic nature of supply and demand and fuzzy parameters for fixed costs, the model was developed and applied under five distinct scenarios, as detailed in Table 5. This table presents numerical values alongside triangular fuzzy membership functions representing fixed costs at minimum, mode, and maximum levels. The model evaluates the effects of supply and demand fluctuations on total costs, unmet demand, environmental impacts, and inventory risks. These analyses assist decision-makers in making optimal decisions regarding cost management and other critical factors under uncertainty.

Table 5. Scenario Analysis of Supply, Demand, and Costs

Scenario	Supply Conditions (S_i)	Demand Conditions (d_d)	Fuzzy Cost Conditions
First (Optimistic)	Initial value	Initial value	Minimum value (L)
Second (Likely)	15% decrease	15% decrease	Most likely value (M)
Third (Pessimistic)	20% decrease	No change from initial value	Maximum value (U)
Fourth (High Risk)	25% decrease	25% increase	Maximum value (U)
Fifth (Minimum)	20% decrease	20% decrease	Minimum value (L)

Given that the proposed model is a scenario-based multi-objective model, its optimality was first evaluated. In the optimization process of each objective, the optimized objective function values are expected to attain the most desirable state relative to the other objectives. Table 4 reports the optimal values of the economic objective function. As this objective seeks to minimize the total system cost, the value of Z1, in this case, achieves the lowest level compared to when the second through fourth objectives are optimized. Similarly, when the environmental objective is optimized, the values of Z3 are expected to reach their minimum. This property holds for all four optimized objectives. Tables 6 through 9 present the various objective function values under different scenarios, while Figure 5 illustrates the corresponding graphs of the optimized objectives in these scenarios.

Table 6. Economic objective function performance (Z1)

S	Z1	Z2	Z3	Z4
1	3168.89	984000	41061.504	2.615
2	2850.284	1134000	40884.29	3.138
3	4104.506	1134000	40884.29	3.138
4	4926.812	1284000	40844.376	3.138
5	2850.284	1134000	40884.29	3.138

Table 7.Social Objective Function Performance (Z2)

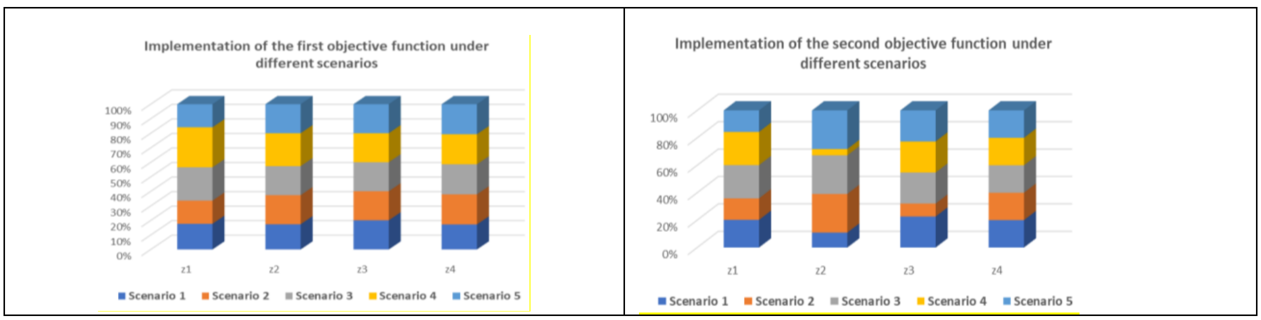
S	Z1	Z2	Z3	Z4
1	5570.979	189600	41058.504	4.184
2	4330.729	489600	17085.233	4.184
3	6697.895	489600	41062.504	4.184
4	6672.895	78960	41060.504	4.184
5	4330.729	489600	41060.504	4.184

Table 8.Performance of the environmental objective function (Z3)

S	Z1	Z2	Z3	Z4
1	19948.405	938400	40843.584	3.138
2	17085.233	1134000	40843.78	4.184
3	22747.541	1134000	40843.78	4.184
4	22770.457	1284000	40843.787	4.184
5	17085.233	1134000	40843.78	4.184

Table 9.Risk objective function performance (Z4)

S	Z1	Z2	Z3	Z4
1	4095.977	984000	41060.504	2.092
2	3396.552	1134000	41058.504	2.615
3	5414.282	113400	41058.504	2.615
4	4926.812	1284000	41060.504	3.138
5	3396.552	1134000	41058.504	2.615



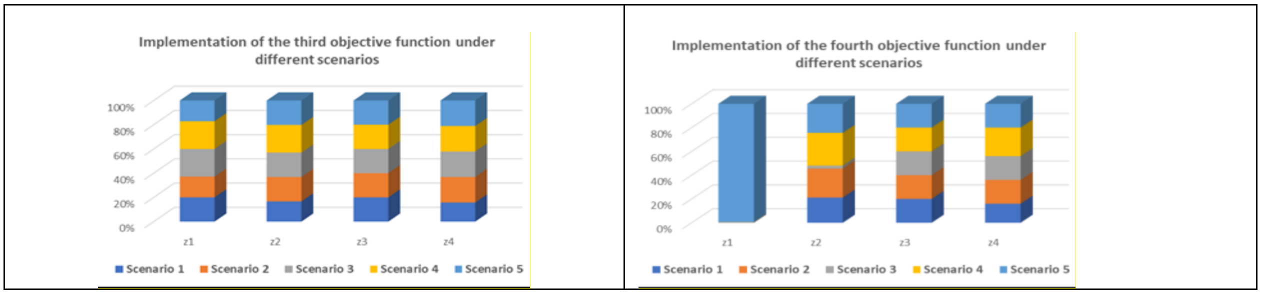


Figure 5. Execution of objective functions under different scenarios

The graphs in Figure 5 demonstrate that different scenarios, including supply, demand, and cost fluctuations, influence the objective functions' performance. Notably, the second and fourth objective functions exhibit a greater relative stability in response to these variations. In contrast, the first and third objective functions demonstrate a heightened sensitivity to scenario changes. These findings underscore the importance of effectively managing uncertainties and optimizing resource allocation to enhance supply chain efficiency and sustainability. Table 10 presents the results derived from solving the model across five distinct scenarios. The costs and the number of facilities utilized have increased and decreased according to the corresponding changes in supply and demand.

Table 10. Results of model variables in five different scenarios

Details		Scenario One	Second scenario	Third scenario	Fourth scenario	Scenario Five
Cost of purchasing biomass		73.48	100.555	158.287	179.225	54.041
Cost of establishing warehouses		355.063	355.063	402.89	395.45	384.01
Cost of establishing drying plants		200.05	230.015	340.5	340.5	170
Cost of water purification		43.63	43.63	48.09	48.09	43.63
Cost of transporting water		365.048	365.048	402	438.23	365.048
Cost of establishing pre-processing centers		602.726	652.365	1002.726	1003.087	502.005
Cost of establishing biogas facilities		606.798	631.61	808.662	915.627	446.226
Cost of renting vehicles		210.925	196.945	210.937	219.857	183.127
Amount of biomass purchased		60.576	60.564	60.576	68.59	44.552
Amount of demand		378	328	378	428	278
Unmet demand		189	164	189	214	139
Environmental impact (measured as CO_2 emissions)		41056.504	41061.13	41059.504	41057.504	41058.504
Number of biomass collection farms		2	2	2	3	2
Number of active storages constructed		1	1	1	2	-
Number of active rented storage units		4	4	5	4	5
Number of active pre-processing centers	Capacity 40 Ton	--	--	--	--	--
	Capacity 60 Ton	1	1	1	--	1
	Capacity 90 Ton	--	--	1	1	--
Number of active biogas facilities		1	1	1	1	1

As illustrated in Table 10, variations in demand and cost fluctuations significantly influence the number of facilities utilized within the model. In the first through third scenarios, which account for diverse supply and demand conditions and incorporate fuzzy cost assessments, facilities are established in proportion to these variations. In the fourth scenario, characterized by the highest demand, products are harvested from three farms, resulting in the establishment of a pre-processing center with a capacity of 90 tons per day, as well as the construction of two warehouses and the rental of four additional warehouses.

Conversely, no storage facilities are constructed in the fifth scenario, which reflects the lowest supply and demand figures alongside the least fuzzy costs. Moreover, the costs associated with water treatment and transportation fluctuate based on usage across all scenarios. Figure 6 presents the graphs illustrating changes in facility costs across the different scenarios. As expected, fluctuations in supply and demand in these scenarios lead to corresponding increases or decreases in the costs associated with the established facilities. Notably, the costs of pre-treatment centers and biogas facilities represent a significant portion of the overall expenditures.

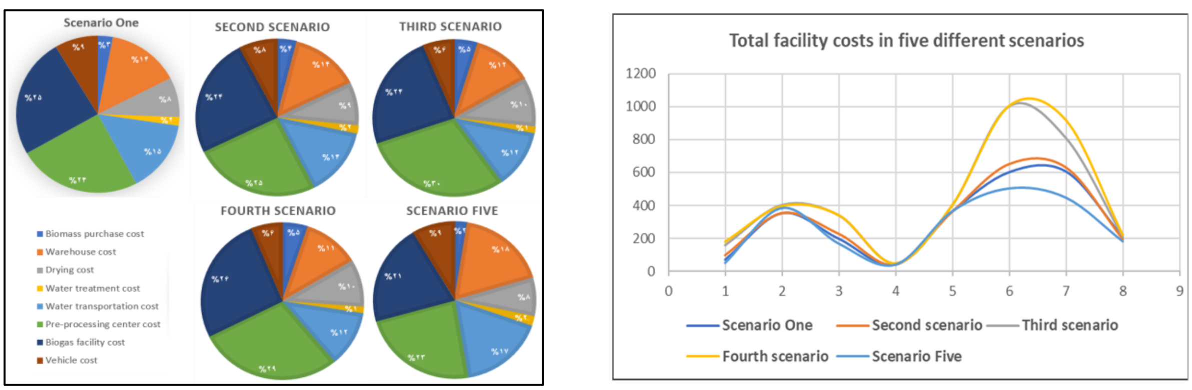


Figure 6. Comparing cost trends in different scenarios

Figure 7 comprehensively analyzes various supply chain indicators across different time periods. Scenarios three and four incur the highest costs compared to the other scenarios, primarily attributable to increased demand and the selection of fuzzy maximum costs. In contrast, scenario five, characterized by the lowest supply, demand, and cost, exhibits the most favorable cost outcome. Similar patterns are observed in water consumption costs, where scenario five reflects the lowest costs while scenario four incurs the highest. Overall, costs remain moderate and exhibit greater stability in scenario one. The fluctuations in inventory risk throughout the scenarios reveal a significant increase in risk for specific scenarios and stages. This escalation may be attributed to supply-demand asymmetry, unpredictable resource supply fluctuations, or transportation constraints.

The number of facilities utilized in the model varies according to each scenario. In the second and third scenarios, there is a significant increase in established facilities, which may indicate a need for further expansion of supply and distribution infrastructure to meet rising demands. In contrast, scenarios one and five, which exhibit a more gradual increase in facilities, represent more optimal strategies for resource allocation and infrastructure utilization, ultimately aimed at reducing costs and enhancing efficiency. Notably, the highest level of unmet demand occurred in scenario four, characterized by the model encountering the most significant demand coupled with the lowest supply.

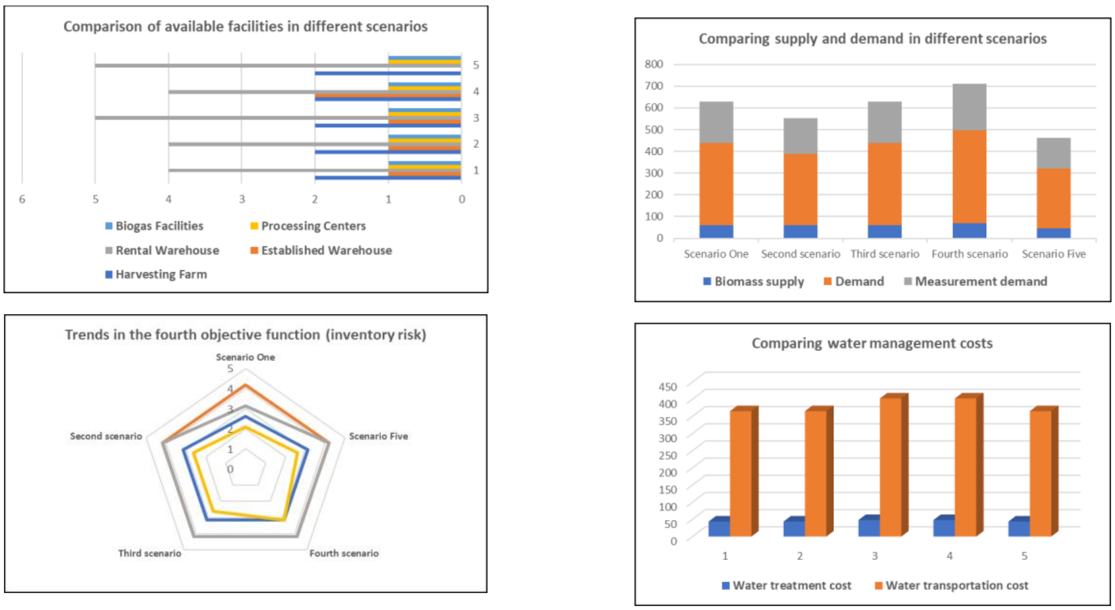
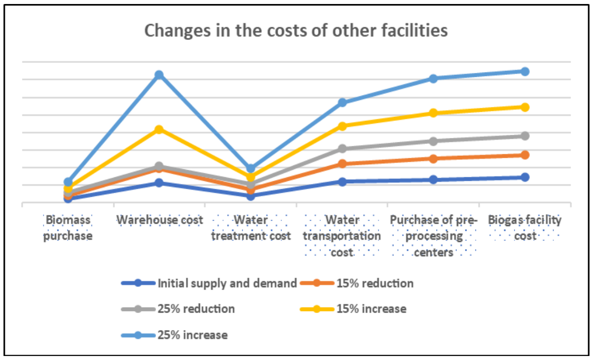


Figure 7. Comparison of key indicators of the research model in different scenarios

Sensitivity Analysis: Sensitivity analysis is a fundamental tool for evaluating the stability and reliability of optimization models. It plays a crucial role in identifying and understanding the effects of variations in input parameters on outcomes (Ransikarbum & Pitakaso, 2024). This study's sensitivity analysis is concerned explicitly with variations in the costs of dryers and vehicles incorporated into the model and the minimum agreed-upon parameter for electricity generation. By reducing the moisture content of biomass, dryers not only mitigate fermentation and exothermic reactions that can result in heat generation and fire during storage but also lower transportation costs. This functionality enhances the safety of biomass storage and diminishes the fire risk.

This study investigates the effects of 15% and 25% fluctuations in supply and demand and the application of fuzzy averages to fixed costs on cost variations. The findings indicate that increases in supply and demand are associated with significant rises in costs related to dryers and vehicles. Conversely, reductions in these parameters result in a decrease in costs. This pattern is also observed for other facility costs, highlighting their susceptibility to change. This analysis enhances our understanding of how sensitive costs are to fluctuations in supply and demand, which can facilitate the optimization of economic and technical decisions in biofuel production processes. Figure 8 illustrates the observed changes in costs.



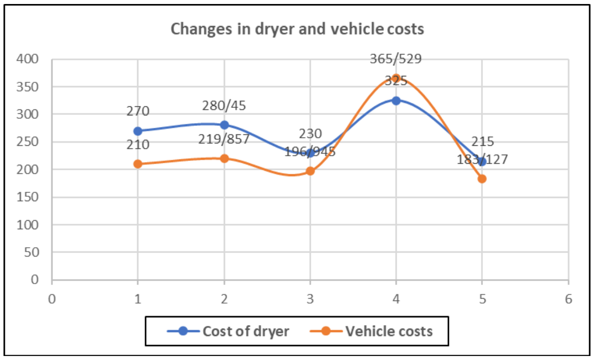


Figure 8. Cost sensitivity analysis to changes in supply and demand

In addition to the observed changes in costs, as illustrated in Figure 9, adjustments to the minimum agreed-upon electricity production for the community (d_min) parameter—specifically, a reduction of 15% or an increase of 25%—will result in proportional changes to the levels of unmet demand. In other words, fluctuations in this parameter directly influence the volume of unmet demand. This analysis underscores the significant impact that variations in the d_min parameter can have on unmet demand, highlighting the necessity of incorporating these changes into decision-making and planning processes.

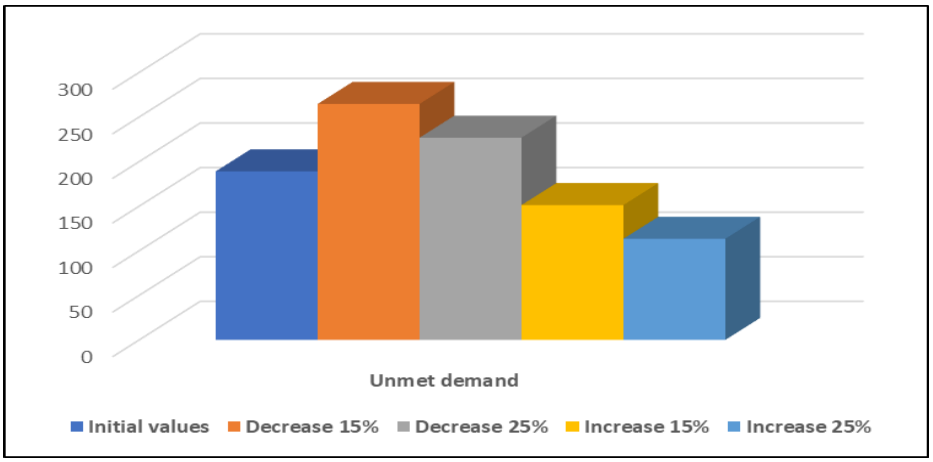


Figure 9. The impact of fluctuations in the minimum agreed electricity parameter on the amount of unmet electricity demand

Discussion

The growing global demand for energy and the problems caused by fossil fuels have further emphasized the necessity of utilizing renewable energy sources such as biomass. To ensure the sustainable supply of these resources, designing and optimizing the supply chain with innovative decisions regarding facility location and distribution is essential for guaranteeing network sustainability and efficiency (Awino et al., 2024). This study proposed a multi-objective optimization model under uncertainty with fuzzy parameters to design the biofuel supply chain. In this model, three objectives—total cost, unmet demand, and environmental impacts—were developed to address the key dimensions of the sustainability paradigm, along with one objective dedicated to reducing warehouse risk. Supply and demand parameters were modeled as stochastic variables. At the same time, facility fixed costs were represented as fuzzy variables to more accurately capture the uncertainties and ambiguities inherent in supply chain processes and support optimal decision-making.

The multi-objective mathematical model was solved using the ε-constraint method. The results in Table 3 indicate that multiple points were generated along the Pareto frontier by varying the ε values for each objective, each representing the most optimal balance achievable among conflicting objectives. These results allow decision-makers to select optimal options based on existing priorities and constraints, enhancing the decision-making process.

Scenario modeling was conducted under five different supply, demand, and fuzzy cost conditions, as shown in Table 4. Initially, the optimization results for each objective function were evaluated separately. Optimization of the economic objective resulted in reduced overall system costs and the minimum possible value for Z1. Similarly, Z3 values reached their lowest point in optimizing the environmental objective. These variations demonstrate that the model can effectively achieve the best outcomes for each objective while maintaining an optimal balance across different goals.

The results of implementing various scenarios, discussed in the Findings section, reveal that supply, demand, and costs significantly impact supply chain performance. Scenarios with increased demand and costs naturally generated the highest expenses, whereas scenarios with minimal supply and demand minimized costs. This highlights the importance of optimizing resources and allocating infrastructure appropriately to reduce costs and improve efficiency. Furthermore, fluctuations in warehouse risk and the need for facility expansion in specific scenarios underscore the importance of effective risk management and infrastructure improvement in response to growing demand. Finally, the model demonstrated that a strategic balance must be maintained among supply, demand, and infrastructure to prevent unmet demand and preserve supply chain efficiency.

Conclusion

As noted in the introduction, wastewater as a water source offers a sustainable solution to reducing pressure on natural water resources. This research showed that this approach not only optimizes water resources but also reduces operational costs, improves system efficiency, and serves as an innovative initiative in resource management under water scarcity, thereby enhancing the performance of the supply chain. Based on the results of the sensitivity analysis, it is recommended that decision-makers incorporate changes in supply, demand, and cost parameters into planning processes. Effective demand management and adjusting electricity production strategies can reduce both costs and unmet demand. In the proposed model of this study, infrastructure facilities—including warehouses, preprocessing centers, biogas plants, vehicles, and water pipeline transfers—were considered dynamically. Developing flexible infrastructure can reduce costs, mitigate risks, and improve performance under uncertainty, enabling managers and decision-makers to manage better economic fluctuations and system efficiency in planning and resource allocation processes.

This broad flexibility in the model allows managers to optimally allocate resources according to supply, demand, and costs fluctuations, and to refine strategic decisions with greater accuracy and efficiency. Therefore, it is recommended that this dynamic feature be utilized in planning and resource allocation processes to effectively reduce costs and maximize the performance of infrastructure systems when facing economic and environmental fluctuations. Moreover, establishing flexible infrastructure can reduce risks and improve performance under uncertain conditions.

The present research, by developing a fuzzy multi-objective model, has focused on reducing costs and environmental impacts and considered warehouse risk management and water resource optimization. While previous studies have primarily emphasized cost reduction and greenhouse gas emission mitigation, such as Zhou et al. (2023), who concentrated solely on cost reduction, and Huang et al. (2024) and Mondal et al. (2023), who addressed uncertainty management using fuzzy approaches, this study contributes by integrating fuzzy facility fixed costs into a multi-objective model, offering a more realistic simulation of actual conditions, and improving the analysis of supply and demand impacts on supply chain performance. Through five-scenario modeling, the results demonstrated that supply and demand variations significantly affect costs and supply chain performance. This finding aligns with the study of Langholtz et al. (2024), who examined the effects of drought and climate change. However, this study emphasized the direct benefits of water resource management and wastewater utilization in reducing costs and enhancing sustainability. By applying the ε-constraint method and Pareto frontier analysis, the study provided an effective decision-making tool for optimal choices. Compared with Bahmani et al. (2024), the proposed model—focused on dynamic infrastructure design and intelligent risk management—demonstrated greater flexibility in addressing uncertainty and environmental changes.

This study further showed that scenario-based modeling of supply and demand conditions allows for a comprehensive analysis of their impacts on supply chain performance. Using wastewater and sewage sludge in the proposed model reduced pressure on natural resources and improved economic and environmental efficiency—a dimension less explored in studies such as Langholtz et al. (2024). The findings, supported by the ε-constraint method and Pareto frontier analysis, provided decision-makers with optimal options aligned with their priorities. Compared with studies such as Bahmani et al. (2024), the proposed model offered greater flexibility for addressing uncertainties by emphasizing dynamic infrastructure design and risk reduction.

The limitations of this study include assumptions embedded in the model that may not fully reflect the complexities of real-world conditions, thereby failing to capture dynamic uncertainties comprehensively. Moreover, solving the model in GAMS required extended computational time due to the complexity of the problem, which limited the rapid analysis of scenarios. Without a comprehensive analysis of social dimensions, the primary focus on economic and environmental aspects is another limitation.

For advancing future research, it is suggested that the model be evaluated across multiple time periods to assess its long-term impacts. Applying spatio-temporal models with GIS-based approaches in Iran can significantly enhance facility location optimization and distribution network design. Furthermore, examining social and cultural dimensions—particularly the impact of biofuel supply chains on local communities and the creation of employment opportunities in rural areas—holds special importance.

Data Availability Statement

Data available on request from the authors.

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Ethical considerations

The authors have witnessed the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy.

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Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work.

References

Abbasi, E., Abu Noori, A., & Mohammadzadeh, M. (2011). Economic evaluation of bioethanol production from sugarcane waste. *Financial Economics*, 161–194. (in Persian).

Abbasi, M., & Pishvaee, M. S. (2019). A mathematical model for optimization in the biofuel supply chain network based on microalgae: A case study of Iran. *1st National Conference on Optimization and Novel Solution Methods*. (in Persian).

Abbasi, M., Pishvaee, M. S., & Mohseni, S. (2021). Third-generation biofuel supply chain: A comprehensive review and future research directions. *Journal of Cleaner Production*, *323*, 129100. (in Persian). https://doi.org/10.22075/jme.2022.23463.2096

Abdali, H., Sahebi, H., & Pishvaee, M. (2021). The water-energy-food-land nexus at the sugarcane-to-bioenergy supply chain: A sustainable network design model. *Computers & Chemical Engineering, 145*, 107199. https://doi.org/10.1016/j.cherd.2022.02.028

Ali, I., & Govindan, K. (2023). Extenuating operational risks through digital transformation of agri-food supply chains. *Production Planning & Control*, *34*(12), 1165–1177. https://doi.org/10.1080/09537287.2021.1988177

Arabi, M., & Yaghoubi, S. (2024). A Lagrangian relaxation approach for algae-based biofuel supply chain network design under uncertainty and pricing issue. *Environmental Science and Pollution Research*, 1–21. https://doi.org/10.1007/s11356-024-35428-7

Awino, F. B., & Apitz, S. E. (2024). Solid waste management in the context of the waste hierarchy and circular economy frameworks: An international critical review. *Integrated Environmental Assessment and Management*, *20*(1), 9–35. https://doi.org/10.1002/ieam.4866.

Bahmani, P., Sadrabadi, M. H. D., Makui, A., & Jafari-Nodoushan, A. (2024). An optimization-based design methodology to manage the sustainable biomass-to-biodiesel supply chain under disruptions: A case study. *Renewable Energy*, 120626. https://doi.org/10.1016/j.renene.2024.120626

Bayramzadeh, S., & Saeedi, M. (2019). Design and planning of a dynamic integrated supply chain network for advanced hydrocarbon biofuels and oil refineries considering financial flows. *Energy Policy and Planning Research, 2*(5), 97–143. (in Persian).

Datta, A., Hossain, A., & Roy, S. (2019). An overview on biofuels and their advantages and disadvantages. *Renewable and Sustainable Energy Reviews, 50,* 1234–1246. https://doi.org/10.14233/ajchem.2019.22098

Duc, D. N., Meejaroen, P., & Nananukul, N. (2021). Multi-objective models for biomass supply chain planning with economic and carbon footprint consideration.*EnergyReports*,*7*,6833-6843. https://doi.org/10.1016/j.egyr.2021.12.139

Eslampanah, A., Jafarnezhad Chaghooshi, A., Heidary Dehu'i, J., & Taghizadeh Yazdi, M. R. (2023). Designing an industrial waste reverse supply chain network using an intelligent vehicular ad hoc network (VANET): A Iranian automotive industry case study. *Industrial Management*, *15*(3), 447–477. (in Persian). https://doi.org/10.22059/imj.2023.363361.1008069

Fathi, M., Pahlevanzadeh, M. J., Safariniya, A., & Raeisi Nafchi, S. (2024). Designing a sustainable closed-loop supply chain network for automobile tires using a multi-objective mathematical programming approach: A case study. Journal of Green Development Management Studies, 3(1), 223–244. (in Persian). https://doi.org/10.22077/jgdms.2024.7174.1068

Flores-Sigüenza, P., López-Sánchez, V., Mosquera-Gutiérrez, J., Llivisaca-Villazhaya, J., Moscoso-Martínez, M., & Guamán, R. (2025). Fuzzy Optimization and Life Cycle Assessment for Sustainable Supply Chain Design: Applications in the Dairy Industry. *Sustainability*, *17*(12), 5634.https://doi.org/10.3390/su17125634.

Ghadge, A., Er Kara, M., Moradlou, H., & Goswami, M. (2020). The impact of Industry 4.0 implementation on supply chains. *Journal of Manufacturing Technology Management*, *31*(4), 669–686. https://doi.org/10.1108/JMTM-10-2019-0368

Ghassemi, A., & Scott, M. J. (2021). *A mathematical approach to improve energy-water nexus reliability using a novel multi-stage adjustable fuzzy robust approach*. In *Progress in Intelligent Decision Science: Proceedings of IDS 2020* (pp. 115–123). *Springer Cham*. https://doi.org/10.1007/978-3-030-66501-2_9

Ghorbani, N., Aghahosseini, A., & Breyer, C. (2020). Assessment of a cost-optimal power system entirely based on renewable energy for Iran by 2050 – Achieving zero greenhouse gas emissions and overcoming the water crisis. *Renewable Energy*, *146*, 125–148. (in Persian). https://doi.org/10.1016/j.renene.2019.06.079

Ghozatfar, A., & Yaghoubi, S. (2023). A cooperation approach for nexus among biofuel, compost, and water in waste supply chain under risk aversion: A case study. *Computers & Chemical Engineering*, *177*, 108334. https://doi.org/10.1016/j.compchemeng.2023.108334

Gilani, H., & Sahebi, H. (2024). Optimizing sustainable multiple biomass-to-biofuel conversion network with integrated water resource management utilizing data-driven robust planning. *Energy Conversion and Management: X*, *24*, 100727. (in Persian). https://doi.org/10.1016/j.ecmx.2024.100727

Gilani, H., Sahebi, H., & Oliveira, F. (2020). Sustainable sugarcane-to-bioethanol supply chain network design: A robust possibilistic programming model. *Applied Energy*, *278*, 115653. (in Persian). https://doi.org/10.1016/j.apenergy.2020.115653

Gital, Y., & Bilgen, B. (2024). Biomass supply chain network design under uncertainty, risk and resilience: A systematic literature review. *Computers & Industrial Engineering*, *189*, 110270. https://doi.org/10.1016/j.cie.2024.110270

Gomez, A., Rodrigues, M., Montanes, C., Dopazo, C., & Fueyo, N. (2011). The technical potential of first-generation biofuels obtained from energy crops in Spain. *Biomass and Bioenergy*, *35*(5), 2143–2155. https://doi.org/10.1016/j.biombioe.2011.02.009

Habib, M. S., & Hwang, S.-J. (2024). Developing sustainable, resilient, and responsive biofuel production and distribution management system: A neutrosophic fuzzy optimization approach based on artificial intelligence and geographic information systems. *Applied Energy*, *372*, 123683. https://doi.org/10.1016/j.apenergy.2024.123683

Habibi, F., Chakrabortty, R. K., & Abbasi, A. (2023). Towards facing uncertainties in biofuel supply chain networks: A systematic literature review. *Environmental Science and Pollution Research*, *30*(45), 100360–100390. (in Persian). https://doi.org/10.1007/s11356-023-25845-7

https://doi.org/10.1016/j.amc.2009.03.037

Huang, X., Ji, L., Xie, Y., & Luo, Z. (2024). Robust optimization of regional biomass supply chain system design and operation with data-driven uncertainties. *Food and Bioproducts Processing*. https://doi.org/10.1016/j.fbp.2024.11.021

Huang, X., Ji, L., Yin, J., & Huang, G. (2024). Optimal design, robust regional bioethanol supply chain operational management, and various technological choices and uncertainty fusions. *Computers & Chemical Engineering, 182,108565*. https://doi.org/10.1016/j.compchemeng.2023.108565

International Energy Agency. (2021). *CO_2 emissions from fuel combustion: Highlights 2021*. IEA. https://www.iea.org

Iranian Ministry of Energy. (2018). *Iran's energy industry and electricity sector report* (in Persian). Ministry of Energy of Iran. http://www.moe.gov.ir

Jakubowski, M. (2022). Cultivation potential and uses of Paulownia wood: A review. *Forests, 13*(5), 668. https://doi.org/10.3390/f13050668

Jana, D. K., Bhattacharjee, S., Dostál, P., Janková, Z., & Bej, B. (2022). Bi-criteria optimization of cleaner biofuel supply chain model by novel fuzzy goal programming technique. *Cleaner Logistics and Supply Chain, 4,* 100044. https://doi.org/10.1016/j.clscn.2022.100044

Jiménez, M., Arenas, M., Bilbao, A., & Rodríguez, M. V. (2007). Linear programming with fuzzy parameters: An interactive method resolution. *European Journal of Operational Research, 177*(3), 1599–1609. https://doi.org/10.1016/j.ejor.2005.10.032

Kazemi Miyangaskari, M., Mehrregan, M. R., Safari, H., Keyvanpour, S., & Dehghan Nayeri, M. (2023). Designing a fuzzy multi-objective optimization model of a closed-loop supply chain aimed at supplier selection and order allocation (case study: food retail company in Iran). *Industrial Management Studies, 21*(69), 1–42. (in Persian). https://doi.org/10.22054/jims.2023.70278.2815

Kiani Mavi, R., Semiari, M., Hosseini Shekarabi, S. A., Kiani Mavi, N., Moshkdanian, F., Nikravesh, A., & Golsorkhi, S. (2025). Multi-Objective Optimization of a Three-Level Sustainable Food Supply Chain: Modeling the Impact of Government Subsidies. *Global Journal of Flexible Systems Management*, *26*(3), 571–600. (in Persian). https://doi.org/10.1007/s40171-025-00454-y

Koçar, G., & Civaş, N. (2013). An overview of biofuels from energy crops: Current status and future prospects. *Renewable and Sustainable Energy Reviews, 28,* 900–916. https://doi.org/10.1016/j.rser.2013.08.022

Langholtz, M., Webb, E., Preston, B. L., Turhollow, A., Breuer, N., Eaton, L., King, A. W., Sokhansanj, S., Nair, S. S., & Downing, M. (2014). Climate risk management for the US cellulosic biofuels supply chain. *Climate Risk Management, 3,* 96–115. https://doi.org/10.1016/j.crm.2014.05.001

Maharana, D., Kommadath, R., & Kotecha, P. (2023). An innovative approach to the supply-chain network optimization of biorefineries using metaheuristic techniques. *Engineering Optimization, 55*(8), 1278–1295. https://doi.org/10.1080/0305215X.2022.2080204

Mahjoub, N., Sahebi, H., Mazdeh, M., & Teymouri, A. (2020). Optimal design of the second and third generation biofuel supply network by a multi-objective model. *Journal of Cleaner Production, 256,* 120355. (in Persian). https://doi.org/10.1016/j.jclepro.2020.120355

Mavrotas, G. (2009). Effective implementation of the ε-constraint method in multi-objective mathematical programming problems. *Applied mathematics and computation*, *213*(2), 455-465.

Mohammadi, A. S., Alem Tabriz, A., & Pishvaee, M. S. (2018). Designing a green closed-loop supply chain network with financial decisions under uncertainty. *Industrial Management Journal*, *10*(1), 61–84. (in Persian). https://doi.org/10.22059/imj.2018.240867.1007303

Mohammadi, T., Sajadi, S. M., Najafi, S. E., & Taqizadeh Yazdi, M. R. (2022). Optimization of a smart supply chain under vendor-managed inventory policy with IoT-related technology selection. *Industrial Management*, *14*(3), 458-483. (in Persian). https://doi.org/10.22059/IMJ.2022.343552.1007948

Mohseni, E., & Mohamadi, D. (2025). Integrated Optimization of Biofuel Supply Chain: A Fuzzy Logic-Based Approach. *Journal of Industrial Management Perspective*, *15*(2), 177–201. (in Persian). https://doi.org/10.48308/jimp.15.2.177

Mohseni, S., & Pishvaee, M. S. (2016). A robust programming approach towards design and optimization of microalgae-based biofuel supply chain. *Computers & Industrial Engineering*, *100*, 58–71. (in Persian). https://doi.org/10.1016/j.cie.2016.08.003

Mollahosseini, A., Hosseini, S. A., Jabbari, M., Figoli, A., & Rahimpour, A. (2017). Renewable energy management and market in Iran: A holistic review on current state and future demands. *Renewable and Sustainable Energy Reviews*, *80*, 774–788. (in Persian). https://doi.org/10.1016/j.rser.2017.05.236

Mondal, A., Giri, B. K., & Roy, S. K. (2023). An integrated sustainable bio-fuel and bio-energy supply chain: A novel approach based on DEMATEL and fuzzy-random robust flexible programming with Me measure. *Applied Energy*, *343*, 121225. https://doi.org/10.1016/j.apenergy.2023.121225

Murillo-Alvarado, P. E., & Ponce-Ortega, J. M. (2024). Optimal planning of biofuel supply chains incorporating temporality of unconventional bioresources. *Environment, Development and Sustainability*, *26*(3), 7715–7733. https://doi.org/10.1007/s10668-023-03028-z

Murillo-Alvarado, P. E., Guillén-Gosálbez, G., Ponce-Ortega, J. M., Castro-Montoya, A. J., Serna-González, M., & Jiménez, L. (2015). Multi-objective optimization of the supply chain of biofuels from residues of the tequila industry in Mexico. *Journal of Cleaner Production*, *108*, 422–441. https://doi.org/10.1016/j.jclepro.2015.08.052

Nozari, H., Nassar, S., & Szmelter-Jarosz, A. (2025). Fuzzy multi-objective optimization model for resilient supply chain financing based on blockchain and IoT. *Digital*, *5*(3), 32. (in Persian). https://doi.org/10.3390/digital5030032

Pan, A., Xu, S., & Zaidi, S. A. H. (2024). Environmental impact of energy imports: Natural resources income and natural gas production profitability in the Asia-Pacific Economic Cooperation Countries. *Geoscience Frontiers*, *15*(2), 101756. https://doi.org/10.1016/j.gsf.2023.101756

Pandey, V. C., Bajpai, O., & Singh, N. (2016). Energy crops in sustainable phytoremediation. *Renewable and Sustainable Energy Reviews*, *54*, 58–73. https://doi.org/10.1016/j.rser.2015.09.078

Paul, S., Mazumder, C., & Mukherjee, S. (2024). Challenges faced in commercialization of biofuel from biomass energy resources. *Biocatalysis and Agricultural Biotechnology, 103312*. https://doi.org/10.1016/j.bcab.2024.103312

Petridis, K., Grigoroudis, E., & Arabatzis, G. (2018). A goal programming model for a sustainable biomass supply chain network. *International Journal of Energy Sector Management*, *12*(1), 79–102.

Qadir, S. A., Al-Motairi, H., Tahir, F., & Al-Fagih, L. (2021). Incentives and strategies for financing the renewable energy transition: A review. *Energy Reports*, *7*, 3590–3606. https://doi.org/10.1108/IJESM-09-2017-0002

Rahbari, M., Khamseh, A. A., & Mohammadi, M. (2023). A novel multi-objective robust fuzzy stochastic programming model for sustainable agri-food supply chain: case study from an emerging economy. *Environmental Science and Pollution Research*, *30*(25), 67398-67442. (in Persian). https://doi.org/10.1007/s11356-023-26305-w1

Rahmandoust, A., Hafezalkotob, A., Rahmani Parchikolaei, B., & Azizi, A. (2023). Designing a multi-objective stable mathematical model for routing municipal waste collection vehicles. *Industrial Management*, *15*(4), 680–709. (in Persian). https://doi.org/10.22059/imj.2023.350291.1007997

Ramírez-Arpide, F. R., Demirer, G. N., Gallegos-Vázquez, C., Hernández-Eugenio, G., Santoyo-Cortés, V. H., & Espinosa-Solares, T. (2018). Life cycle assessment of biogas production through anaerobic co-digestion of nopal cladodes and dairy cow manure. *Journal of Cleaner Production, 172*, 2313–2322. https://doi.org/10.1016/j.jclepro.2017.11.192

Ransikarbum, K., & Pitakaso, R. (2024). Multi-objective optimization design of sustainable biofuel network with integrated fuzzy analytic hierarchy process. *Expert Systems with Applications, 240,* 122586. https://doi.org/10.1016/j.eswa.2023.122586

Rashid Khan, H. U., Awan, U., Zaman, K., Nassani, A. A., Haffar, M., & Abro, M. M. Q. (2021). Assessing hybrid solar-wind potential for industrial decarbonization strategies: Global shift to green development. *Energies, 14*(22), 7620. https://doi.org/10.3390/en14227620

Seidl, P. R., & Goulart, A. K. (2016). Pretreatment processes for lignocellulosic biomass conversion to biofuels and bioproducts. *Current Opinion in Green and Sustainable Chemistry, 2,* 48–53. https://doi.org/10.1016/j.cogsc.2016.09.003

Suresh, S., Barboza, A. B., Ashwini, K., & Dinesha, P. (2024). Optimization of ANN Models Using Metaheuristic Algorithms for Prediction of Tailpipe Emissions in Biodiesel Engine. *Heat Transfer.* https://doi.org/10.1002/htj.22972

Tong, K., Gleeson, M. J., Rong, G., & You, F. (2014). Optimal design of advanced drop-in hydrocarbon biofuel supply chain integrating with existing petroleum refineries under uncertainty. *Biomass and Bioenergy, 60,* 108–120. https://doi.org/10.1016/j.biombioe.2012.11.026

Wachyudi, T., Daryanto, A., Machfud, M., & Arkeman, Y. (2020). Biofuel supply chain risk mitigation strategy framework: Expert interview based approach. *Journal of Industrial Engineering and Management, 13*(1), 179–194. https://doi.org/10.3926/jiem.3127

Wang, M., Ji, L., Xie, Y., & Huang, G. (2024). Regional bioethanol supply chain optimization with the integration of GIS-MCDM method and quantile-based scenario analysis. *Journal of Environmental Management, 351,* 119883. https://doi.org/10.1016/j.jenvman.2023.119883

Wassie, S. B. (2020). Natural resource degradation tendencies in Ethiopia: A review. *Environmental Systems Research, 9*(1), 1–29. https://doi.org/10.1186/s40068-020-00180-0

Yousefloo, A., Babazadeh, R., Mohammadi, M., Pirayesh, A., & Dolgui, A. (2023). Design of a robust waste recycling network integrating social and environmental pillars of sustainability. *Computers & Industrial Engineering, 176,* 108970. https://doi.org/10.1016/j.cie.2023.108970

Zarei, M., Shams, M. H., Niaz, H., Won, W., Lee, C.-J., & Liu, J. J. (2022). Risk-based multistage stochastic mixed-integer optimization for biofuel supply chain management under multiple uncertainties. *Renewable Energy, 200,* 694–705. (in Persian). https://doi.org/10.1016/j.renene.2022.09.012

Zarrinpour, N., & Khani, A. (2019). Design of second-generation green fuel supply chain from corn waste under uncertainty conditions. *The 16th International Conference on Industrial Engineering*. (in Persian).

Zema, D. A., Bombino, G., Andiloro, S., & Zimbone, S. M. (2012). Irrigation of energy crops with urban wastewater: Effects on biomass yields, soils and heating values. *Agricultural Water Management, 115,* 55–65. https://doi.org/10.1016/j.agwat.2012.08.003

Zhang, X., & Vesselinov, V. V. (2016). Energy-water nexus: Balancing the tradeoffs between two-level decision makers. *Applied Energy, 183*, 77–87. https://doi.org/10.1016/j.apenergy.2016.08.153

Zhang, Y., Jiang, Y., Zhong, M., Geng, N., & Chen, D. (2016). Robust optimization on regional WCO-for-biodiesel supply chain under supply and demand uncertainties. *Scientific Programming, 2016*, 1087845. https://doi.org/10.1155/2016/1087845

Zhao, X., Ke, Y., Zuo, J., Xiong, W., & Wu, P. (2020). Evaluation of sustainable transport research in 2000–2019. *Journal of Cleaner Production, 256*, 120404. https://doi.org/10.1016/j.jclepro.2020.120404

Zhou, T., Zhou, T., Li, Z., Aviso, K. B., Tan, R. R., Jia, X., & Wang, F. (2024). Multi-objective optimization of straw-based bio-natural gas supply chains considering cost, CO2 emission, and safety. *Journal of Cleaner Production, 449*, 141759. https://doi.org/10.1016/j.jclepro.2024.141759