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Sustainability assessment of biomass-based energy supply chain using multi-objective optimization model

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Abstract

In recent years, population growth and lifestyle changes have led to an increase in energy consumption worldwide. Providing energy from fossil fuels has negative consequences, such as energy supply constraints and overall greenhouse gas emissions. As the world continues to evolve, reducing dependence on fossil fuels and finding alternative energy sources becomes increasingly urgent. Renewable energy sources are the best way for all countries to reduce reliance on fossil fuels while reducing pollution. Biomass as a renewable energy source is an alternative energy source that can meet energy needs and contribute to global warming and climate change reduction. Among the many renewable energy options, biomass energy has found a wide range of application areas due to its resource diversity and easy availability from various sources all year round. The supply assurance of such energy sources is based on a sustainable and effective supply chain. Simultaneous improvement of the biomass-based supply chain's economic, environmental and social performance is a key factor for optimum network design. This study has suggested a multi-objective goal programming (MOGP) model to optimize a multi-stage biomass-based sustainable renewable energy supply chain network design. The proposed MOGP model represents decisions regarding the optimal number, locations, size of processing facilities and warehouses, and amounts of biomass and final products transported between the locations. The proposed model has been applied to a real-world case study in Istanbul. In addition, sensitivity analysis has been conducted to analyze the effects of biomass availability, processing capacity, storage capacity, electricity generation capacity, and the weight of the goals on the solutions. To realize sensitivity analysis related to the importance of goals, for the first time in the literature, this study employed a spherical fuzzy set-based analytic hierarchy method to determine the weights of goals.

Keywords Biomass · Bioenergy · Biomass supply chain · Sustainable biomass supply chain · Optimization

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1 Introduction

The global energy demand has prominently shown an upward trend in recent years due to rapid population growth, urbanization, and industrialization (Chyuan & Silitonga, 2020). Current global energy demand is met by various fossil fuels; oil, natural gas, and coal (Liu et al., 2017). Although these resources are commercially developed and relatively inexpensive, they cause various problems, such as price fluctuations, dependency on foreign countries, and greenhouse gas emissions (Cooper et al., 2019). Statista reports that greenhouse gas emissions worldwide from global energy and industrial processes total 36.3 million metric tons in 2021 (Statista, 2022).

The increased concerns about fossil fuels have resulted in a collective interest in developing alternative energy sources and infrastructures. Renewable energy resources have great potential to be a promising alternative for reducing environmental impacts and fossil fuel dependency (Azadeh & Arani, 2016). The International Energy Agency recognizes that promoting renewable energy will provide an environmentally sustainable future (Silva et al., 2018). According to the International Renewable Energy Agency (IRENA), by 2050, renewable energy sources will meet 85% of the energy demand, whose generation rates are expected to increase rapidly (Abraham et al., 2020). The contribution of alternative energy resources to overall electricity production was 13.6% in 2001; it will reach 47.7% in 2040 (Uddin et al., 2021) (Fig. 1).

Solar, hydraulic, geothermal, wind and biomass energy are renewable energy types available in nature and can be easily acquired (Zeren & Akkuş, 2020). Among these sources, biomass obtained from all biogenic organic materials is one of the most versatile energy sources (Nunes et al., 2020). Moreover, biomass has the potential to benefit the environment by lessening CO2 and other toxic gas emissions and enhancing rural employment and agricultural expansion, thereby helping countries achieve sustainable development (Hosen et al., 2022).

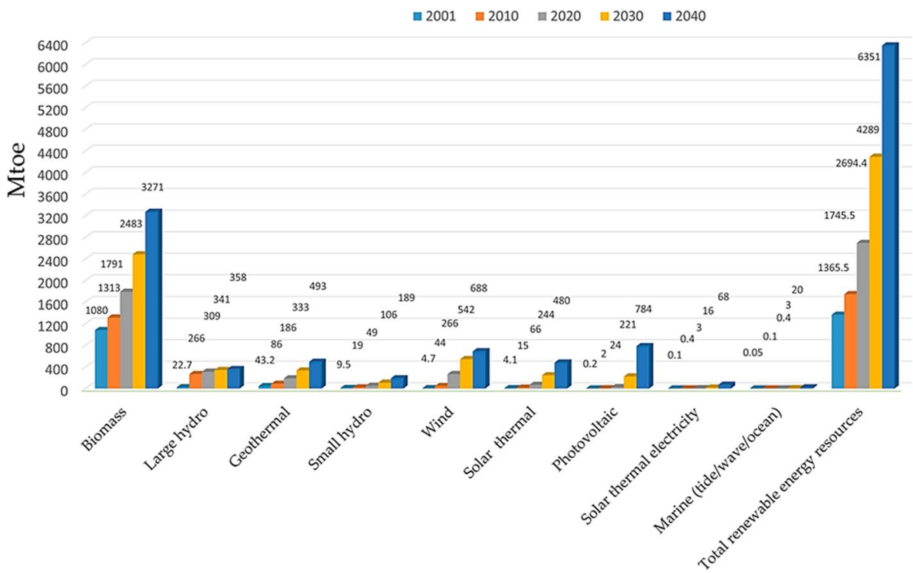

Fig. 1 The renewable energy categories (Uddin et al., 2021)

Biofuels from biomass sources have been used for decades as an alternative to fossil-based fuels (Boro et al., 2022). Biofuels from biomass sources have been used for decades as an alternative to fossil-based fuels. Biofuels are classified into two main categories depending on their source: first- and second-generation biofuels (Ghelichi et al., 2018). First-generation biofuels, produced from starch, sugar, animal fat, and vegetable oils, have been commercialized in some countries due to their cost competitiveness compared to fossil fuels (Kesharwania et al., 2019).

Biomass production is estimated at 146 billion metric tons annually throughout the world, mainly from wild-growing plants (Hosen et al., 2022). However, increased biofuel production seriously threatens the security of the food supply and causes ecological damage, such as biodiversity loss, due to land-use changes (Sadat et al., 2018). On the other hand, second-generation biofuels are produced from solid and liquid municipal waste, forest residues, agricultural waste, manure, and inedible raw materials (Arabi et al., 2019). Therefore, unlike first-generation biofuel production, their production contributes to reduced land-use changes and reduced food and fuel competition.

Biogas, as part of biomass, is recognized in the EU legislation as a renewable source (Kulišić et al., 2015). It is generated by the anaerobic decomposition of biomass (Seyitoglu et al., 2022). Biogas is the most challenging renewable fuel in terms of potential assessment because of its diverse inputs and valuable energy forms available (technical and economic potential) (Kulišić et al., 2015). However, compared to other biofuels, biogas production consumes minimal energy and relies on readily available renewable resources making it a very viable source of energy (Singh et al., 2022).

Biogas, the fourth most abundant energy source globally, has excellent potential as a second-generation biofuel among all renewable energy sources (Gao et al., 2019). It consists of a gas mixture, including typically approximately 50%–70% methane (CH_4), 30%–50% carbon dioxide (CO_2), and traces of impurities generated by anaerobic digestion of organic materials such as animal waste, waste produced by humans, food industry waste, municipal waste, and energy facilities (Boulamanti et al., 2013; Miltner et al., 2020; Singh et al., 2022). Biogas generation through anaerobic digestion provides a renewable energy source that can be used as bioenergy and biofuel and enables the production of high-nutritional-value organic manure (Achinas & Willem Euverink, 2020). Biogas production from organic resources is seen as a measure to reduce greenhouse gas (GHG) emissions in several sectors (Lyng & Brekke, 2019).

It is estimated that biomass energy can meet approximately 25% of global energy needs (Seyitoglu et al., 2022). Among the top countries for generating electricity from biomass during 2015 were the USA (69 TWh), Germany (50 TWh), China (48 TWh), Brazil (40 TWh), and Japan (36 TWh), followed by the UK and India. Furthermore, the International Energy Agency (IEA) estimates that in 2020–2025, the total installed capacity of biomass power plants in Turkey will increase by 630 MW (IEA, 2020). Considering that Turkey's overall installed capacity connected to the electricity grid was 88550.8 MW in 2018, biomass can potentially provide 0.8% of the total installed electrical power demand (Ocak & Acar, 2021).

The bioenergy industry has drawn significant attention in the last decade (Egieya et al., 2019). However, the competitiveness of biomass as an alternative energy source against fossil fuels can only be sustainable if the challenges can be overcome. Sustainability is defined as meeting the present's needs without compromising future generations' ability to meet their own needs. A sustainable supply chain is related to a detailed examination of supply chain activities that affect supply chain parameters in economic, social, and environmental aspects (Mottaghi et al., 2022). However, biogas technology has advantages in waste management, partial control of energy production management, environment, and health compared to other RES. Another benefit of biomass energy is reducing the greenhouse gas effect (Aksay & Tabak, 2022). The EU 28 is planning to reduce 50% reductions in GHGs by 2050. To meet EU target, biofuel is expected to be an important factor in controlling energy consumption in heating, transportation, and electricity generation. In addition, there is still an enormous potential to recover energy from waste disposal sites (Can, 2022; Zhang et al., 2022).

Several studies have been carried out on biomass-based energy supply chain models with only economic aspects, and few of them were subjected to other objectives, such as environmental functions. For example, Cobuloglu and Büyüktahtakin (2014) address the problem using a multi-objective MILP model with objectives considering environmental impacts and maximizing the economic value during its life cycle. Murillo-Alvarado et al. (2015) developed a supply chain for the production of biofuels from the lignocellulosic residues of the tequila industry is formulated as a multi-objective MILP model, which accounts for the simultaneous maximization of the economic and environmental aim of the network. Likewise, Babazadeh et al. (2017) proposed a model to minimize the total costs of the biodiesel supply chain. Also, another goal of their model is to reduce the environmental effect.

A literature review showed that few studies also address the social objectives of designing a biomass supply chain. Miret et al. (2016) presented an optimal design of the biomass supply chain by focusing on multi-objective MILP optimization based on sustainability. In addition to the economic and environmental considerations, Ganev et al. (2021) developed a comprehensive MILP model on social sustainability. The review by Ghaderi et al. (2016) presents that nearly 78% of the studies considered economic issues, and only 13% investigated economic and environmental. Not surprisingly, only 1% of the studies focused on social impacts. The paper highlighted the need for comprehensive approaches since only 5% of the studies include all three economic, environmental, and social sustainability objectives.

Considering these facts, an effective design of a sustainable supply chain network is necessary to overcome the challenges such as high moisture content, seasonal availability, and uncertainties in demand and policy of biomass raw materials to increase bioenergy use and ensure effective decision-making (Egieya et al., 2019). An optimized supply chain design, which provides the integration and coordination of all activities involved in the process, from the procurement of biomass raw materials to final value-added products, contributes to increasing the efficiency and profitability of bioenergy generation (Akhtari et al., 2019).

1.1 The objective of the study

This study aims to develop an optimized configuration of a biomass supply chain to minimize the total cost and environmental impact in all chain echelons. Furthermore, the model simultaneously seeks to maximize the biomass network's social impact. To achieve these objectives, this study proposes a multi-objective mixed-integer linear programming (MILP) model for the infrastructure of the bioenergy conversion process, which determines the amount of biomass and flows of finished- or semi-products transported between the tiers of the chain, supply and demand points. Furthermore, the model specifies the capacities and locations of warehouses and processing facilities to be established in the entire network. Therefore, this problem can be considered a multi-objective capacitated location/

allocation problem. The goal programming (GP) method is used to overcome conflicting goals due to the multi-objective structure. This method provides a set of compromise solutions that minimizes deviations from target values and thus addresses the problem with a more realistic approach.

1.2 The contributions of the study

The main contributions and novelties of the present study are as follows:

- It proposes a multi-objective optimization methodology to support strategic and tactical decision-making in a biomass-based supply chain, considering that the waste biomass resources are natural wealth.
- The multi-objective goal programming model optimizes the supply chain and considers the triple bottom line of sustainability, i.e., economic, environmental, and social objectives.
- It supports food safety by eliminating concerns about using renewable biomass raw materials for energy generation by choosing waste biomass resources as raw materials for biomass-based energy production.
- The model encourages a circular economy that aims to transform waste into new resources as much as possible by using organic fertilizer, a beneficial by-product of the system.
- Data for a real-life case study in the Metropolitan Municipality of Istanbul, Turkey's most populated and most energy-consuming city, are used to validate the proposed model. Therefore, it also provides practical guidelines for policymakers.
- A sensitivity analysis presents the effects of changes in biomass availability, processing capacity, storage capacity, electricity generation capacity, and weights of goals.
- In sensitivity analysis, we used the spherical fuzzy AHP to determine the weight of goals. To the best of our knowledge, this is the first study that used the spherical fuzzy AHP integrated multi-objective goal programming.

The remaining sections of this study cover the following: Sect. 2 provides a comprehensive literature review on biomass-based sustainable design of the supply chain network. In Sect. 3, the problem statement and the MILP model are presented. Section 4 demonstrates the application of the model to a real-world problem. Section 5 gives the results of the study. Policy implications are provided in Sect. 6. Finally, Sect. 7 presents some practical recommendations and implications of possible future research directions.

2 Literature review

The volume of studies on biomass-based supply chains has rapidly increased in recent years because of their potential to be a more sustainable alternative energy resource than fossil fuels. As a result, analytical techniques and simulation methods have been frequently used in the literature for supply chain network optimization. MILP, stochastic mixed-integer linear programming (SMILP), mixed-integer nonlinear programming (MINLP), and multi-objective mixed-integer quadratic programming (MMIQP) have been used to optimize biomass supply chain (BSC) network. The literature review indicates that extensive research has been done on the development of BSC models, and some of the recent models are reviewed in this study.

In BSCs, most researchers have focused on developing single objective models that achieve profit maximization or cost minimization. For instance, Yilmaz Balaman and Selim (2015) developed a multi-period MILP for anaerobic digestion-based BSC. The sensitivity analysis examined the annual operating cost and the effect of using only animal waste biomass in facilities. Paulo et al. (2015) developed a MILP model to design a supply chain network using forest waste as a biomass source for bioenergy production. They conducted sensitivity analyses for uncertain parameters. Sharifzadeh et al. (2015) proposed a MILP model that optimizes net present value throughout the supply chain. Jensen et al. (2017) formulated a MILP model for biogas production through simultaneous anaerobic digestion of manure, sugar beet, and straw. They minimized the cost of a BSC that generates electricity, heat, and natural gas in a cogeneration system as final products. In addition, they conducted sensitivity analyses for price, demand, and subsidies. Han et al. (2023) presented a three-stage game model to study the consumer preference behavior as a decision-making process. Bairamzadeh et al. (2018) presented a MILP model to optimize the total cost of a biofuel supply chain network under various uncertainties, such as biomass conversion technology, biomass yield, and fuel demand. A further study on biomass energy and supply network design was conducted by Yıldız and Ayvaz (2018), which was the premise of the present work. Unlike the current study, the authors modeled and solved the problem with a single objective, cost minimization, for the city of Istanbul, neglecting sustainability concerns regarding the reverse logistics network.

Halim et al. (2019) suggested a MILP model minimizes the cost of producing multiple bioproducts using various technologies. They performed a sensitivity analysis to analyze the effect of biomass resources on the total cost. Dominique et al. (2019) formulated a MILP model that compares costs using two different types of biomass as raw materials, namely Jatropha curcas and Balanites aegyptiaca, the most widely used biomasses in biofuel production. Santibañez-Aguilar et al. (2019) proposed a MILP model that maximizes the economic objectives of a biomass supply chain network based on sugarcane, agave, corn, and rice waste. The facility location was determined using GIS. Ge et al. (2021) proposed a MILP model that minimizes cellulosic biomass-based biofuel supply chain costs.

In recent years, mathematical modeling techniques have been developed by considering the sustainable benefits of BSC management. In addition to economic optimization, creating environmental and social values provides sustainable solutions, thereby making BSCs more competitive in the long term. To this end, Cambero et al., (2015) formulated a multi-objective MILP model of the bioenergy/biofuel supply chain from forest and wood waste. Jonker et al. (2016) formulated a MILP to decrease ethanol production costs between 2012 and 2030 and limit ethanol's greenhouse gas emission intensity. Amore and Bezzo (2016) proposed a multi-objective MILP model considering the economic and environmental targets of the supply chain designed to produce bioenergy/bioethanol from corn kernels and residues. Mirkouei et al. (2017) proposed MILP for a sustainable supply chain that addresses the environmental and economic objectives of the supply chain designed to extract biofuels from forest biomass. They conducted sensitivity analyses for the availability of biomass and biorefinery cost parameters.

Osmani and Zhang (2017) presented a MILP to optimize a multi-objective and multi-period sustainable bioethanol supply chain under uncertainties. Likewise, they used the ε-constraint approach to solve conflicting economic, social, and environmental goals. Elisabeth et al. (2018) formulated an uncertain multi-objective MILP to maximize discounted net present value for biofuel production and minimize greenhouse gas emissions and land-use change. They used a point-based *min–max* robust concept to calculate robust Pareto-optimal solutions to solve an uncertain multi-objective optimization model. Rabbani et al. (2018) proposed a multi-objective MILP model that simultaneously optimizes economic growth and social goals in energy plant-based bioenergy supply chain design. Arabi et al. (2019) proposed a multi-period MMIQP under uncertainties to maximize profit and minimize carbon emissions. They used data envelopment analysis (DEA) to evaluate the performance of alternative cities for microalgae harvesting yield. Kristianto and Zhu (2019) proposed a MINLP model for maximizing the supply chain's total profit for biodiesel production using cooking oil and rice straws as raw materials. Díaz-trujillo and Fabricio (2019) presented a multi-objective MILP for biogas and biofertilizer production that considers both economic and environmental impact. They used the Pareto solution to demonstrate the effect of the relationship between profit and greenhouse gas emissions in the analysis of various scenarios created for the sale of purified biogas and purified–unpurified biogas.

Another study was done by Hosseinalizadeh et al. (2019), which developed a multi-period and multi-objective MILP model for biodiesel fuels of various concentrations. The model considered two simultaneous objectives, minimization of facility investment costs and environmental effects, and was solved with the augmented epsilon-constraint method. Gital Durmaz and Bilgen (2020) proposed a multi-objective MILP model that incorporates the two objective functions of maximization of the profit and minimization of the total distance between poultry farms and biogas facilities. Ahmadvand et al. (2021) developed a bi-objective optimization model for the tactical planning of forest-based biomass supply chains. The study determined the trade-offs between the total costs and the possible deviations from the safety stock. Abbasi et al. (2022) proposed a hybrid model comprising genetic algorithms and MILP to address a real-world case where municipal solid waste data belonging to 11 districts located in Tehran, Iran chain was used. The bi-objective model was developed by considering environmental and economic goals simultaneously.

The review of extant literature reveals that the MILP approach is the most common among various mathematical programming techniques in BSC optimization. However, unlike most research, Corsano et al. (2011) presented a MINLP for a sustainable supply chain network design of bioethanol production from sugar cane. A scenario analysis was done to analyze the effects of various parameters on sustainable production and distribution. Čuček et al. (2012) formulated a MINLP to maximize the total profit of the BSC and assess its carbon footprint and environmental impacts. Chen and Fan (2012) focused on a waste biomass-based bioethanol supply chain design based on supply and demand uncertainties. They proposed a two-stage SMILP to minimize the supply chain cost. Gonela et al. (2015) proposed a SMILP for sustainable hybrid production in a bioethanol supply chain based on uncertainties, aiming to maximize economic benefits with social and environmental constraints.

Shabani and Sowlati (2016) proposed a SMILP model to maximize a forest biomass-based supply chain network. The impact of uncertainties was analyzed using a MILP and stochastic MILP model. Santibañez-Aguilar et al. (2016) proposed a multi-objective SMILP model that takes into account environmental and economic goals to control the supply chain of biofuels from various biomass sources. Fattahi and Govindan (2018) developed a SMILP model for a multi-biomass-based biofuel supply chain that addresses three sustainability safeguards. A similar study was developed by Saghaei and Dehghanimadvar (2020), where forest biomass was used. A recent study by Sarker et al. (2019) developed a MINLP to minimize cost when locating biogas facilities. A genetic algorithm (GA) was used as the solution method.

Other studies concerning optimizing modern BSCs use simulation-based techniques. Marvin et al. (2012) proposed a MILP to maximize the net present value of a biomass-based biofuel supply chain for bioethanol production using various agricultural residues. A sensitivity analysis of price uncertainty and Monte Carlo simulation were used to determine the robustness of the supply chain. Paolotti et al. (2017) proposed a simulation model for modeling the economic and environmental goals of the biomass supply chain. Lastly, Akhtari et al. (2019) utilized Any Logic software to compare the effects of inventory management systems' annual demand, cost, and CO_2 emissions on forest-based BSCs using forest waste as the source of biomass.

Salehi et al. (2022) developed a resilient and sustainable biomass supply network with uncertainty in bio-energy demand and disruption in the bio-refinery. They utilized a robust approach to handle the uncertainty in bioenergy demand. Aranguren et al. (2021) suggested a two-stage stochastic model for co-firing biomass supply chain networks. They deployed simulated annealing to solve the presented model. The proposed model is validated by using real data from the northeast region of the USA. Guo et al. (2022) developed a multi-period stochastic programming model for biomass-to-biofuel supply chain network to cope with collectible corn stover removal and farmer participation rates uncertainties. Han et al. (2022) reviewed a collection on the prefabricated construction with supply chain management process. Wu et al. (2022) introduced an agri-biomass supply chain optimization model. They applied the model to a case study in Shandong Province's Dezhou City.

Ge et al. (2021) presented a new cellulosic biofuel supply chain model to minimize total supply chain cost. The developed model was applied to case studies from the state of Illinois in the USA. Allman et al. (2021) suggested deterministic and two-stage stochastic models for biomass waste to energy supply chain optimization with mobile production modules under the biomass quantity and location uncertainties. The presented framework is applied in Minnesota and North Carolina. Aboytes-Ojeda et al. (2022) introduced a stochastic programming framework to optimize the biomass supply chain to minimize the costs of producing biofuels. They presented a novel hub-and-spoke network to take advantage of the economies of scale in transportation and to minimize the effect of poor-quality raw material. The model is validated by an application in Texas.

Kwon et al. (2022) developed a multi-period model of an organic waste-to-biodiesel phased supply chain network to strategically handle variations in the biodiesel demand and organic waste usage over a long-term planning interval. The application of a future organic waste-to-biodiesel supply chain network design case study in South Korea validates the suggested model. Habib et al. (2022) presented a robust programming model to determine the optimal production–distribution quantities and to support facility location and capacity decisions under supply and demand disruption scenarios. They applied the proposed model to a real-world case study. Finally, Ahmadvand and Sowlati (2022) developed a robust optimization model for the forest-based biomass supply chain for syngas production under uncertainties. The model is applied to the real case of a large Kraft pulp mill in British Columbia, Canada.

2.1 Literature gaps

According to the literature mentioned above, few studies on supply chain design for waste biomass consider one or two sustainability dimensions. Also, there is a lack of studies to explore the concurrent economic, social, and environmental impacts and the balance among the sustainability dimensions of waste biomass in a supply chain. In addition, as far as we know, the social impact of local and clean energy use has never been studied in the previous literature.

Further, the literature demonstrates that numerous studies have focused on biofuel conversion with similar biomass raw materials. Therefore, in this study, the application of a multi-objective MILP designed for utilizing animal wastes and fruit and vegetable wastes, which are selected as raw material sources for food and feed security in the production of bioenergy and biofertilizer (organic fertilizer), contributes to the current literature, which simultaneously considers three-pillars of sustainability. Furthermore, the model is applied to real data for the Istanbul metropolitan area, a unique application to the best of our knowledge.

3 Methodology

3.1 Problem statement

This study proposes a multi-objective MILP model for biomass-based sustainable energy supply chain (BS-ESC) network design, considering three aspects of sustainability: economic, environmental, and social. The BSC considered in this study includes four different tiers: raw material suppliers, biomass storage, biogas facilities, and demand points. The structure of a generic sustainable biomass supply chain is shown in Fig. 2.

An integrated BS-ESC structure for sustainable energy includes several processes from suppliers to points of demand. To achieve efficient waste management in the supply chain, cattle manure, laying hen manure, broiler chicken manure, and food waste are used as the inputs to the model. Wastes are gathered from farms, and wholesale vegetable markets are collected

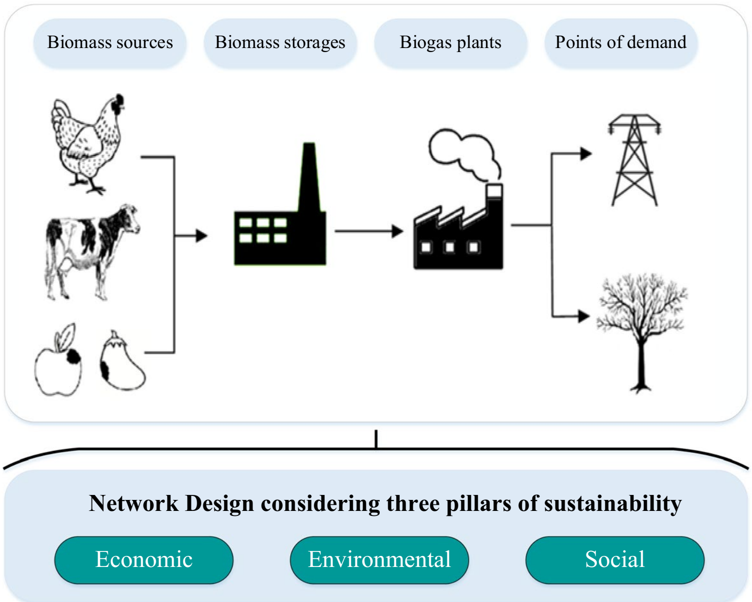

Fig. 2 The general structure of a BS-ESC network

in biomass storage facilities. Then, they are transferred to biogas facilities, where they are fed to a digester that conducts anaerobic digestion. The output of this stage is biogas and highly nutritious fertilizer. Simultaneous anaerobic digestion of waste increases biogas efficiency, contributing to reducing greenhouse gas emissions due to fossil fuel use. On the other hand, the biogas is sent to a cogeneration unit, combined heat and power (CHP), which generates electrical energy and heat as a by-product. Electrical energy is fed into the national electricity network, and the facility uses waste heat as process heat. The digestion residuals are separated into solid and liquid organic fertilizers. The solid one is usually sold to municipalities, whereas the liquid organic fertilizer is used to meet the water needs of the digester.

Various crops in food production have been used as a vital raw material source for bioenergy. However, this has led to critical competition between food and energy, resulting in an unpleasant impact on food security (María et al., 2021; Namany et al., 2019). For this reason, the present study aims to use only waste to generate energy. Therefore, the BS-ESC represents an interconnected integrated system that simultaneously provides organic waste treatment and generation of renewable energy. Additionally, the system serves other purposes, such as reducing greenhouse gas emissions and potential pollutants if carelessly left to the environment. The optimization model for the chain will determine the appropriate system configuration for simultaneously minimizing economic and environmental impact while maximizing social impact throughout the supply chain.

The following assumptions are considered in developing the mathematical model for BS-ESC network design:

- Biogas is produced by wet anaerobic digestion; therefore, water is added to the digester to regulate the total solid content of the feedstock mix.
- Two types of biomasses are used to generate bioenergy: animal waste and wholesale market waste.
- Digestion residual organic solid fertilizer is sold to municipalities for utilization in parks and gardens.
- The electrical energy generated is fed into the national electricity network.
- The capacities of all facilities and warehouses are limited.
- The processing facilities and warehouses may be constructed with different predetermined capacities based on supply.
- Wholesale market waste is stored after size reduction.
- Liquid manure and heat are assumed to be used in digesters but are not included in the mathematical model.
- Wholesale market waste, solid animal waste, and liquid/semi-solid animal waste are stored differently.
- This study was based on 12 counties of Istanbul with the most concentrated biomass sources.
- The coefficients of the objective function are deterministic and known.
- The model is solved using 10% of the total biomass available.
- The discount factor is taken as 0.0824, and the facilities' lifetime is considered 20 years.
- Annual operating costs of facilities and warehouses are 10% of total investment costs.

3.2 Model formulation

This section defines the formulation of the developed model. The notation for the model is presented in Table 1.

3.2.1 Objective functions and constraints

In this subsection, a multi-objective model is presented for the design of anaerobic digestion-based biomass energy supply chains. As stated before, the proposed model includes environmental, economic, and social objectives, which are three aspects of sustainability. The objectives are as follows:

(i) To minimize the total cost,
(ii) To minimize the greenhouse gas emissions (CO_2 equivalent) based on transportation and production activities in the BSC,
(iii) And to maximize the use of clean local energy in the local community.

The economic purpose of the presented model is related to minimizing the total cost of the BS-ESC network, which is a function of investment and operational expenses and generated revenue due to the sales of end products of the system. The related objective function has five parts:

Min Z_1 *= [Investment Costs + Operating Costs + Transport Costs + Biomass Purchase Cost] – Total Income.*

- *Total Income:* The total income (see Eq. 1) has two components: the sale of electrical energy generated in facilities to the national network and the income obtained from the sale of solid organic fertilizer to municipalities.

$$EP \cdot \sum_t EG_t + GP \cdot \sum_t \sum_i g_{ti} \tag{1}$$

- *Investment Costs:* Total investment costs (Eq. 2) have also two components: the investment cost for warehouses and the investment cost for facilities, respectively.

$$Df \cdot \sum_d \sum_c WC_{dc} \cdot x_{dc} + Df \cdot \sum_t \sum_i FC_{tk} \cdot y_{tk} \tag{2}$$

- *Operating Costs:* Total operating cost (Eq. 3) has three components: warehouses' operating cost, facilities' operating cost, and water cost. The first two operating cost components are considered a predefined percentage of the investment cost.

$$IO \cdot \sum_d \sum_c WC_{dc} \cdot x_{dc} + IO \cdot \sum_t \sum_i FC_{tk} \cdot y_{tk} + \sum_t s_t \cdot WP \tag{3}$$

- *Transport Costs:* Total transport costs (Eq. 4) have three components: biomass transported from sources to warehouses, biomass transported from warehouses to facilities, and the cost of solid organic fertilizer transported from biogas facilities to points of demand.

$$\sum_b TC_b \cdot \left(\left(\sum_r \sum_d b_{rdb} \cdot Ma_{rd} \right) + \left(\sum_d \sum_t b_{dtb} \cdot Mb_{dt} \right) \right) + \left(\sum_t \sum_i g_{ti} \cdot TC_{ti} \cdot Me_{ti} \right) \tag{4}$$

- *Biomass Purchase Costs:* Biomass purchase costs (Eq. 5) comprise the amounts and costs of biomass sent from supply regions.

Table 1 The notation used in the mathematical model

Index	Definition
D	Set of storage locations, where $D = \{1, 2,3,\ldots,d\}$
T	Set of facility locations $T = \{1, 2,3,\ldots t\}$
B	Set of types of biomass $B = \{1, 2,3,\ldots,b\}$
R	Set of supply regions $R = \{1, 2,3,\ldots r\}$
K	Set of alternative facility capacities $K = \{1, 2,3,\ldots k\}$
C	Capacity of depot/warehouse $C = \{1, 2,3,\ldots c\}$
I	Set of demand points $I = \{1, 2,3,\ldots i\}$
Parameters	
BPC_{tk}	Biomass processing capacity for a facility with capacity k in the tth location [ton]
EGC_{tk}	Electricity generation capacity for a facility with capacity k in the tth location [kWe]
BSC_{dc}	Biomass storage capacity a warehouse with capacity c in the dth location [ton]
AB_{rb}	The amount of the bth type of biomass available in the rth supply region [ton]
BDO_b	Biogas conversion rate of the bth type of biomass [m^3/ton UK]
MO	Methane rate in biogas [%]
BMI	Methane unit energy content of biogas [kWh/m^3]
BEV	The electricity conversion efficiency of biogas in cogeneration unit [%]
GDO_b	Rate manure conversion for the bth biomass [%]
TK_b	Rate of solid matter in the bth type of biomass [%]
UKM_b	Rate of volatile solid matter in the bth type of biomass [%]
KEU	Greenhouse gas emission due to electricity generation [kg CO_2 equivalent/kWh]
KET	Greenhouse gas emission due to biomass transport [kg CO_2 equivalent/ton/km]
KEI	Annual electricity need of a residence
Ma_{rd}	Distance between the rth supply region and the dth storage location [km]
Mb_{dt}	Distance between the dth storage and the tth facility location [km]
Me_{ti}	Distance between the tth facility and the ith point of demand [km]
FC_{tk}	Investment cost of a facility with capacity k in the tth location [€/kWh]
WC_{dc}	Investment cost of a warehouse with capacity c in the dth location [€/ton]
TC_b	Unit transport cost of the bth type of biomass [€/ton-km]
TC_{ti}	Unit transport cost of digestion residue organic solid manure [€/ton-km]
EP	Price of electricity [€/kWh]
GP	Price of solid organic manure [€/ton]
WP	Price of water[€/ton]
PC_b	Cost to purchase for the bth type of biomass [€]
IO	Predefined investment cost ratio for operating costs [%]
SKO	The conversion ratio for solid organic manure in the separator [%]
SSO	The conversion ratio for liquid organic manure in the separator [%]
Df	Annual discount factor [%]
$TK_{\min}$	Minimum solid biomass content in the digester [%]
$TK_{\max}$	Maximum solid biomass content in the digester [%]
Decision variables	
y_{tk}	If a facility with capacity k is to open in the tth location, it is 1; otherwise, it is 0
x_{dc}	If a warehouse with capacity c is to open in the dth location, it is 1; otherwise, it is 0
b_{rdb}	The amount of the bth type of biomass transported from the rth supply Region to the dth storage [ton]

Table 1 (continued)

Index	Definition
b_{dtb}	The amount of the *b*th type of biomass transported from the *d*th storage to the *t*th facility [ton]
g_{ti}	The amount of solid organic manure transported from the *t*th facility to the *i*th supply region [ton]
W_t	The amount of digestion waste organic liquid manure in the *t*th facility [ton]
BG_t	The amount of biogas generated in the *t*th facility location [m^3]
EG_t	The amount of electricity generated in the *t*th facility [kWh]
s_t	The amount of water used in the *t*th facility [ton]
PBE_t	The number of total residences using bioenergy *t*th location

$$\sum_r \sum_d \sum_b PC_b \cdot b_{rdb} \tag{5}$$

The environmental objective of the model is to minimize greenhouse gas (CO_2) emissions of the sustainable biomass-based energy supply network. The second objective has two components: biomass transport and greenhouse gas emissions caused by bioenergy production.

Min Z_2 = *Greenhouse Gas Emissions of Bioenergy Production* + *Greenhouse Gas Emissions of Biomass Transport.*

- *Greenhouse Gas Emissions of Bioenergy Production:* The greenhouse gas emissions caused by bioenergy production (Eq. 6) represent CO_2 emissions due to biogas facilities producing bioenergy.

$$KEU \sum_t EG_t \tag{6}$$

- *Greenhouse Gas Emissions of Biomass Transport:* The greenhouse gas emissions of biomass transport (Eq. 7) have two components: CO_2 emissions due to the transport of biomass from supply centers to warehouses and CO_2 emissions due to the transport of biomass from warehouses to biogas facilities.

$$KET \cdot \left(\sum_r \sum_d \sum_b b_{rdb} + \sum_r \sum_d \sum_b b_{dtb} \right) \tag{7}$$

The social objective of the model considers the vital importance of the environment, which is one of the seven primary articles of ISO 26000 Social Responsibility Management Standard. Thus, the social objective was to maximize meeting the electrical energy needs of residences from bioenergy in such a manner that it contributes to clean and domestic energy needs:

Max Z_3 = Amount of Total Residences using bioenergy.

- *Amount of Total Residences using Bioenergy:* The total number of residences using bioenergy (Eq. 8) is calculated based on the electricity generated.

$$PBE_t = \sum_t \frac{EG_t}{KEI} \tag{8}$$

Equations (9–22) indicate the constraints of the presented model, which can be grouped as demand constraints, flow of material constraints, facility capacity constraints, production constraints, digester conversion ratio constraints, and, lastly, natural constraints for problem variables of being nonnegative and integer.

$$\sum_d b_{rdb} \le AB_{rb} \quad \forall r, \forall b \tag{9}$$

$$\sum_r b_{rdb} = \sum_r b_{dtb} \quad \forall b, \forall d \tag{10}$$

$$\sum_r \sum_b b_{dtb} \le \sum_c BSC_{dc} \cdot x_{dc} \quad \forall d \tag{11}$$

$$\sum_d \sum_b b_{dtb} \le \sum_k BPC_{tk} \cdot y_{tk} \quad \forall t \tag{12}$$

$$\sum_d \sum_b b_{dtb} \cdot BDO_b \cdot UKM_b \cdot TK_b = BG_t \quad \forall t \tag{13}$$

$$BG_t \cdot BMI \cdot BEV \cdot MO = EG_t \quad \forall t \tag{14}$$

$$\sum_k EGC_{tk} \cdot y_{tk} \ge EG_t \quad \forall t \tag{15}$$

$$SKO \cdot \sum_d \sum_b b_{dtb} \cdot GDO_b = \sum_i g_{ti} \quad \forall t \tag{16}$$

$$SSO \cdot \sum_d \sum_b b_{dtb} \cdot GDO_b = W_t \quad \forall t \tag{17}$$

$$\left(\sum_d \sum_b TK_b \cdot b_{dtb} \right) \le TK_{\max} \cdot \left(\sum_d \sum_b b_{dtb} + s_t \right) \quad \forall t \tag{18}$$

$$\left(\sum_d \sum_b TK_b \cdot b_{dtb} \right) \ge TK_{\min} \cdot \left(\sum_d \sum_b b_{dtb} + s_t \right) \quad \forall t \tag{19}$$

$$y_{tk}, x_{dc} \in \{0, 1\} \tag{20}$$

$$b_{dtb}, b_{rdb}, g_{ti}, BG_t, EG_t, s_t, W_t \geq 0 \tag{21}$$

Equation (9) assures that the amount of biomass obtained from a supply source does not exceed the amount of biomass available. Similarly, Eq. (10) represents the constraint by which the quantity of biomass sent from biomass supply regions to warehouses equals the amount of biomass shipped from warehouses to facilities.

Equation (11) is a capacity constraint and assures that the amount of biomass sent from biomass supply regions to warehouses is not higher than the total capacity of warehouses. Similarly, Eq. (12) provides that the amount of biomass shipped from warehouses to facilities is not higher than the total capacity of facilities.

Equation (13) calculates the amount of biogas produced and assigns it to a new variable, while Eq. (14) converts the biogas used to produce electricity. Equation (15) formulates that electrical energy generation at facilities does not exceed the technical capacity limit of facilities for electrical energy generation.

Equations (16) and (17) calculate the amount of solid and liquid organic fertilizers produced in facilities. Equations (18) and (19) have been derived from this equation, and they provide that the total solid content for wet digestion of biomass slurry is within technical limits in digesters. In addition, both constraints estimate the amount of water inserted into the digester. Lastly, Eq. (20) shows binary integer decision variables, and Eq. (21) indicates nonnegative decision variables.

3.2.2 Solution procedure

As stated before, the main aim of this study is to find a compromise providing the best possible agreement among three conflicting objectives that contribute to developing an efficient supply chain for bioenergy production. In solving the multi-objective supply chain problem, the GP method, which was first developed by Charnes et al. (1955) and was more clearly defined by Charnes and Cooper (1961), is used (Tamiz et al., 1998). GP is a widely used multi-objective decision-making approach. Its popularity is mainly because of its flexibility, making it possible to solve decision problems involving various criteria, imperfect data, and many decision variables and constraints.

In GP models, deviations between the achievement of goals are minimized, meaning that a particular function of unwanted deviation variables is minimized (Rodr, 2002). In this study, weighted GP was used. In the weighted GP algorithm, goal functions are weighted by considering their importance levels. An objective function representing all objective functions is created as the weighted sum of the three functions representing various goals (Verma et al., 2009). The equation of the new objective function, in which three objective functions given in Sect. 3.2.1 are simultaneously considered, is shown below:

$$\min Z = w_1 \cdot d_1^+ + w_2 \cdot d_2^+ + w_3 \cdot d_3^- \tag{22}$$

where w_1, w_2, *and* w_3 are weights of the three objective functions. The three weights are assumed to be equal. d_1^+, d_2^+ d_3^+ and d_1^-, d_2^- d_3^- are deviation variables of goals: d_1^+, d_2^+ d_3^+ indicate positive deviation, and d_1^-, d_2^- d_3^- represent negative deviations from the goal.

In addition to the constraints given in Sect. 3.2.1, Eqs. (23–25) represent new constraints of the model. The new constraints are created by adding deviation variables to each objective function.

The representation of the economic objective function denoted as Z_1 is given as a new constraint:

$$\sum_b TC_b \cdot \left(\left(\sum_r \sum_d b_{rdb} \cdot Ma_{rd} \right) + \left(\sum_d \sum_t b_{dtb} \cdot Mb_{dt} \right) \right) + \left(\sum_t \sum_i g_{ti} \cdot TC_{ti} \cdot Me_{ti} \right) +$$
$$IO \cdot \sum_d \sum_c WC_{dc} \cdot x_{dc} + IO \cdot \sum_t \sum_i FC_{tk} \cdot y_{tk} + \sum_r \sum_d \sum_b TC_b \cdot b_{rdb} + \sum_t s_t \cdot SP +$$
$$Df \cdot \sum_d \sum_c WC_{dc} \cdot x_{dc} + Df \cdot \sum_t \sum_i FC_{tk} \cdot y_{tk} - EP \cdot \sum_t EG_t - GP \cdot \sum_t \sum_i g_{ti} - d_1^+ + d_1^- = G_1 \tag{23}$$

The representation of the environmental objective function indicated as Z_2 is given below as a new constraint:

$$KEU \cdot \sum_t EG_t + KET \cdot \left(\sum_r \sum_d \sum_b b_{rdb} + \sum_r \sum_d \sum_b b_{dtb} \right) - d_2^+ + d_2^- = G_2 \tag{24}$$

The equation of the environmental objective function denoted as Z_3 is given as a new constraint:

$$KEU \cdot \sum_t PBE_t + d_3^+ + d_3^- = G_3 \tag{25}$$

4 Case study

To validate the proposed model, a case study is carried out for BS-ESC network design in Istanbul, which has the largest population in Turkey and dominance over its surrounding area in terms of Turkey's economic and social development.

The food demand, which has sharply increased recently because of population growth, has increased the amount of organic waste generated. Uncontrolled waste storage harms natural resources and results in greenhouse gas emissions threatening the environment and human health. Wastes, which have adverse effects on the environment, can be used as a source of biomass for energy generation in bioenergy facilities instead of being discarded as garbage and disposed of in landfills. Istanbul has vast potential for organic waste, such as animal and wholesale market waste. Production of energy and anaerobic digestion residue organic fertilizer is possible as a result of utilizing waste as biomass. To achieve this, a comprehensive decision-making tool is required that guarantees both the commercialization and sustainable development of bioenergy generation.

Compared to other types of energy, bioenergy may be obtained from purpose-grown products or trees in a very intensive land process. Unsustainable bioenergy production can have negative consequences, such as food shortages and land use competition. As shown in Fig. 3, 60% of the bioenergy supply in 2030 will come from waste and residues that do not require land use (IEA, 2022).

The proposed study presents a sustainable biomass-based energy supply chain model for three aspects of sustainable development and real-world assumptions to address these issues. The model is applied to selected counties of Istanbul, which are determined depending on the animal and wholesale waste intensity. Silivri, Çatalca, Arnavutköy, Büyükçekmece, Başakşehir, Bayrampaşa, and Eyüp counties were chosen on the European side, whereas Beykoz, Sancaktepe, Şile, Pendik, and Tuzla counties were determined on the Anatolian side, resulting in a total of 12 counties.

The model considers these counties as potential regions for biomass supply, warehouses, and bioenergy facilities. Candidate locations for points of demand are determined independently from these counties. There are 23 supply regions within these counties because there is more than one supply point in some areas. The regions are determined based on the current economic activities that generate biomass waste. The candidate counties selected for facilities are Silivri, Arnavutköy, Başakşehir, Şile, and Tuzla. Likewise, the candidate locations for warehouses are assumed to be in Silivri, Arnavutköy, Başakşehir, Şile, Tuzla, and Çatalca. Beyoğlu and Kadıköy counties are selected as points of demand. The related candidate locations of different facilities in the city are shown in Fig. 4.

4.1 Biomass sources

In this study, four types of biomass waste are considered raw materials to be processed in biogas facilities: cattle manure, laying hen manure, broiler chicken manure, and wholesale market waste. To achieve high biogas efficiency, animal manure, and wholesale market wastes are simultaneously processed through an anaerobic digestion process in biogas facilities. The potential biomass waste data for counties were gathered from the Ministry of Food, Agriculture, and Livestock of Turkey. The amount of waste per animal was calculated based on 34 kg/day for cattle and 0.16 kg/day for chickens (Sözer & Yaldiz, 2011). The wholesale market waste data were taken from Istanbul Metropolitan Municipality Wholesale Market Directorate. Table 2 presents the properties of biomasses discussed in this study.

4.2 Transportation

In this study, we selected road transportation among various transportation modes because the national transportation infrastructure in the city is suitable for biomass and fertilizers.

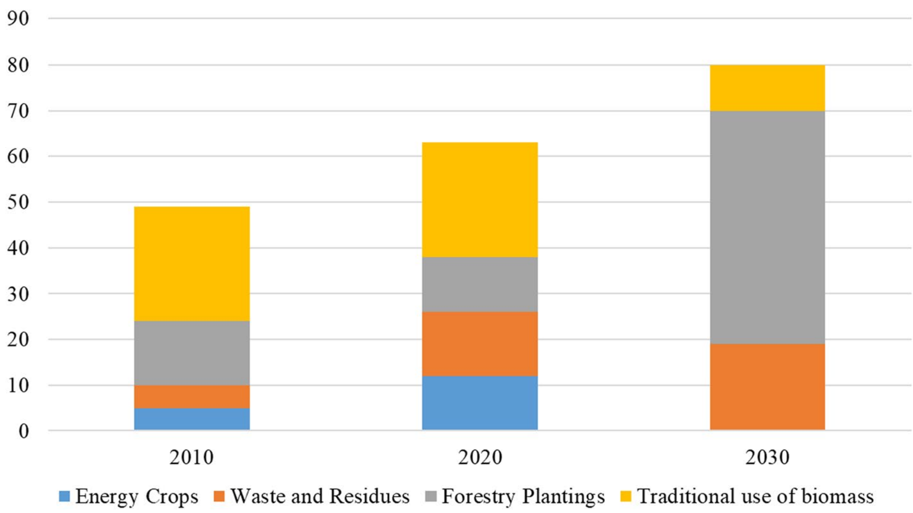

Fig. 3 Global bioenergy supply (IEA, 2022)

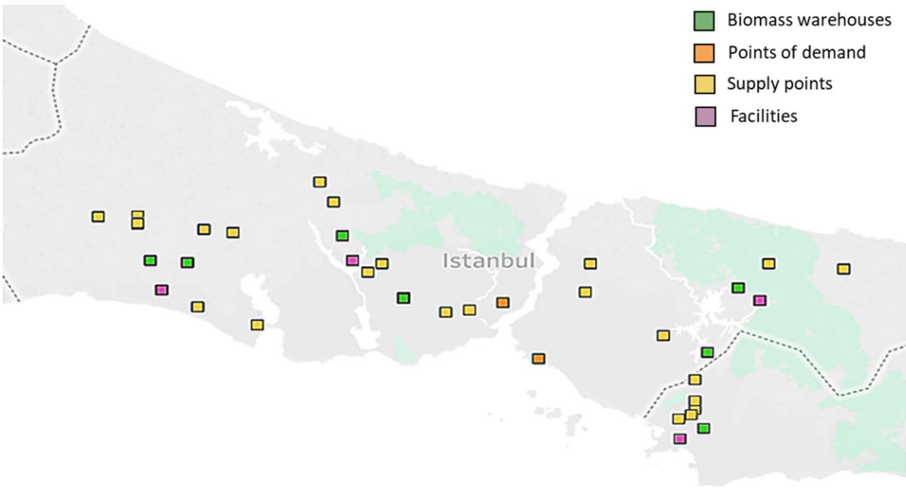

Fig. 4 Locations of facilities in Istanbul

The related data were provided at the county level. The Euclidean distance was used to approximate distances between the locations determined in the counties.

Cattle manure is transported based on a cost of 0.05 €/t-km, whereas wholesale market waste is transported based on 0.03 €/t-km (Poeschl et al., 2010). Laying hen manure and broiler manure are assumed to be transported at the same price as cattle manure. The greenhouse gas emission value due to transport is taken as 0.053 kg CO_2 equivalent/t-km (Čuček et al., 2010).

4.3 Biomass warehouses and biogas facilities

Alternative locations of biomass warehouses and biogas facilities are selected as close as possible to biomass supply regions to minimize transport costs. In this study, biogas produced due to anaerobic digestion in biogas facilities is used only to generate electricity and heat energy. Therefore, we assumed that the electrical power generated in the cogeneration system is wholly distributed to the national electricity network based on the local

Table 2 Properties of waste biomasses

Biomass source	Total solid (%)	Biogas efficiency (m^3/t VS)	Volatile solid (%)	References
Cattle manure	16.3	340	81	(Avcioğlu & Türker, 2012; Zhang et al., 2013)
Poultry manure (Egg)	24.5	450	75	(Avcioğlu & Türker, 2012; Keskin et al., 2018)
Poultry manure (Broiler)	50	550	65	(Avcioğlu & Türker, 2012)
Wholesale market wastes	12.7	450	84.9	(Ganesh et al., 2015; Scano et al., 2014)

electricity demand. In contrast, the researchers assumed that the generated heat energy is used to satisfy various heat needs of the facility.

Three different capacity levels are assumed for biogas facilities: 4000 t/month, 6000 t/month, and 14,000 t/month. The installed capacity for electrical energy generation of cogeneration systems corresponding to each capacity level is 1000 kWe, 2000 kWe, and 3000 kWe, respectively, which are usually studied in the literature. The cogeneration systems' electrical and heat energy efficiencies are taken as 41% and 44%, respectively (Lijó et al., 2017). The greenhouse gas emission value due to electrical energy production in biogas facilities is 0.00023 kg CO_2 equivalent/kWh (DECC, 2017).

4.4 Economic parameters

The electricity generated by biogas facilities is fed into the national electricity network for 0.103 €/kWh. The model uses the electricity price specified in Law No. 5346 on the Use of Renewable Energy Resources for Generating Electrical Energy for biomass-based production facilities. It is assumed that anaerobic digestion residue is sold to solid organic fertilizer points of demand at 8.4 €/t.

Investment costs generally do not change linearly according to facility size; thus, the relationship among investment costs corresponding to facility capacities is defined in Eq. (26) (Amigun & Von Blottnitz, 2010). Facility capacity costs are estimated from the literature based on the facility investment cost corresponding to 1000 kWe facility capacity (Kremljak, 2017).

$$\frac{C_1}{C_2} = \left(\frac{Q_1}{Q_2}\right)^n \tag{26}$$

where Q_2 and C_2 indicate the capacity and investment cost of the referenced facility, respectively, and Q_1 and C_1 show the capacity and investment cost of the new facility. Exponent n indicates the capacity cost factor.

The purchase cost of cattle manure is 5.5 €/t, and the purchase cost of laying hen and broiler chicken manure is 6.5 €/ton (Chinese et al., 2014). The purchase cost of wholesale waste is taken as 5 €/ton.

5 Experimental results

This study implemented the multi-objective MILP in GAMS version 25.0.3 and solved it using a CPLEX solver (v12.8). The solution of the MILP model is performed on a Windows 10 Pro 64-bit operating system, running on hardware with an Intel Core i7 2.60 GHz processor and 16 GB RAM. The multi-objective model consists of 27 discrete and 736 continuous variables at the current model settings.

The total deviation from the target, the optimal solution of the applied model, is 135314.909. The model deviated by 135314.909 from the target of minimizing the sum of the investment, operating, transport, and biomass purchase costs required to establish biogas facilities and biomass warehouses. This value indicates that the deviation exceeds the optimal result of the single-objective model by 135314.909 €. Accordingly, the value of the first objective function is found to be 245988.98 €. The model does not deviate from the target of minimizing the CO_2 emissions generated during the transport of biomass sources and the formation of the final product. In other words, the second goal of 179636.943 kg CO_2 equivalent is realized precisely. Thus, the second objective function is calculated as 314951.852 kg CO_2 equivalent. There is no deviation from the target of maximizing the use of renewable energy sources by more residences due to electricity generation in the biogas facility. The total of 5013 homes indicates that the result of the single-objective target is optimal. Table 3 presents the results of the proposed model.

Due to economies of scale, the solution indicates that the biogas facility has to have a 14,000 t/month capacity among alternatives; 4000, 6000, and 14,000 t/month. Therefore, the facility is opened only in Başakşehir among five candidate facility locations. The electrical energy generation capacity of the facility is 3000 kWe. Moreover, three biomass warehouses, each with a 6000 t/month capacity, are established in three counties. The optimum locations for these warehouses are determined as Arnavutköy, Başakşehir, and Çatalca. Figure 5 illustrates the biomass flow to established biomass warehouses.

In the model, the following amounts of biomass raw materials are sent to biogas facility number 3 in Başakşehir, 54631.083 t/year from biomass warehouse number 2 in Arnavutköy, 52686.737 t/year from biomass warehouse number 3 in Başakşehir, and 32783.503 t/year from biomass warehouse number 6 in Çatalca. The digestion residual solid organic fertilizer is only sent to the point of demand number 2 in Beyoğlu such that the distance will be close to the biogas facility to prevent the cost and environmental effects caused by long-distance transport. Figure 6 illustrates the biomass flow from biomass warehouses to

Table 3 Optimal values of decision variables

Warehouses opening, capacity, and location decisions			
x_{dc}	$x_{21}=1$, $x_{31}=1$, $x_{61}=1$, $x_{dc}=0$ (for all others)		
Facility opening, capacity, and location decisions Facility opening, capacity, and location decisions			
y_{tk}	$y_{33}=1$, $y_{tk}=0$ (for all others)		
Amount of waste biomass sent to warehouses from biomass supply regions (ton/year)			
b_{rdb}	$b_{1,6,1}=23215.38$	$b_{10,3,1}=4965.24$	$b_{19,3,2}=659.92$
	$b_{2,2,1}=28153.32$	$b_{11,3,1}=3623.72$	$b_{20,6,2}=3905.71$
	$b_{3,2,1}=23359.34$	$b_{12,6,2}=5662.40$	$b_{21,3,3}=264.55$
	$b_{4,2,1}=3050.378$	$b_{13,2,2}=61.32$	$b_{22,3,4}=1013.90$
	$b_{5,3,1}=7524.183$	$b_{14,2,2}=6.71$	$b_{23,3,4}=1520.80$
	$b_{6,3,1}=11576.05$	$b_{15,3,2}=17.52$	Values of all other $b_{dtp}=0$
	$b_{7,3,1}=8337.04$	$b_{16,3,2}=12.20$	
	$b_{8,3,1}=1788.28$	$b_{17,3,2}=64.24$	
	$b_{9,3,1}=11228.57$	$b_{18,3,2}=90.52$	
Amount of waste biomass sent to the facility from warehouses (ton/year)			
b_{dtb}	$b_{2,3,1}=54563.05$	$b_{3,3,3}=264.55$	Values of all other $b_{dtp}=0$
	$b_{2,3,2}=68.04$	$b_{3,3,4}=2534.70$	
	$b_{3,3,1}=49043.08$	$b_{6,3,1}=23215.39$	
	$b_{3,3,2}=844.41$	$b_{6,3,2}=5662.41$	
		$b_{6,3,3}=3905.71$	
Amount of manure sent to the point of demand from the facility (t/year)			
g_{ti}	$g_{3,2}=25009.399$, and all other $g_{ti}=0$		
Amount of electricity generated in the facility (kWh)			
EG_t	$EG_t=18,046,830$		

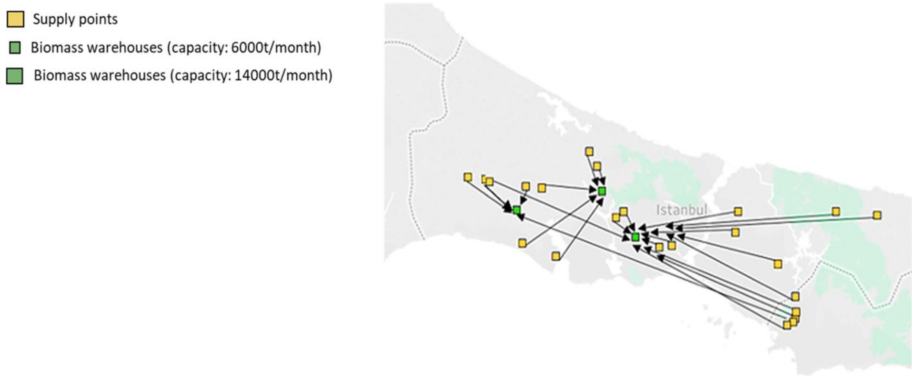

Fig. 5 Supply regions and biomass flow between warehouses

the biogas facility and the solid organic fertilizer flow from the biogas facility to the point of demand. The model allows the establishment of one facility and three warehouses in the European part of Istanbul.

5.1 Sensitivity analysis

In this section, we conduct a sensitivity analysis to analyze the effects of biomass availability, processing capacity, storage capacity, electricity generation capacity, and the weight of goals.

The variability in biomass availability significantly affects CO_2 emissions from transportation and bioenergy production, the number of residences using renewable energy depending on electricity production, and transportation and biomass purchasing costs. A detailed analysis of its impact on various decision variables is described below, taking into account the biomass availability parameter, which is thought to affect the performance of the BS-ESC. The basic model determines the biomass availability as %10 of the existing biomass availability. Sensitivity analysis shows how various decision variables change with different biomass availability percentages: in the

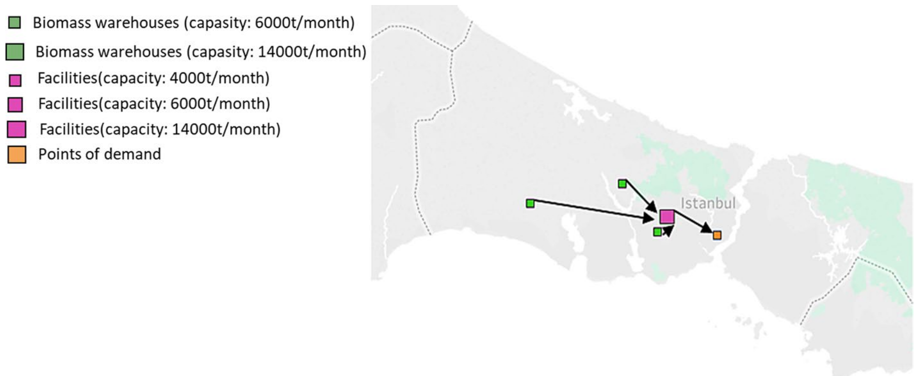

Fig. 6 Biomass and digestion residual flow among warehouses, the facility and point of demand

range of 15% to 55%. Biomass flow was not achieved above 55% due to the insufficient capacity of biomass warehouses.

As shown in Table 4, biomass availability causes changes in the location, number, and capacity of the biomass warehouse and biogas facilities. In addition, the change in biomass availability causes deviations from the economic and environmental objectives, while it does not lead to deviations in the social goals (see Fig. 7). Increased biomass availability drove changes in the optimum value of the objective function and the location, number, and capacity of the biomass warehouse and biogas facilities. More precisely, higher biomass availability increased the capacity and number of biomass warehouses and biogas facilities. However, parallel to the increased biomass availability, the electricity generated increased linearly.

Next, we conduct a set of second sensitivity analyses regarding biomass processing capacity. As given in Table 5, biomass processing capacity increased from 10 to 300%. Table 5 shows the effect of biomass processing capacity on objective functions and decision variables. As can be seen, the economic goal is sensitive to the increase in biomass processing capacity. On the other hand, the environmental and social goals remain almost constant. The biomass processing capacity increasing ratio caused changes in the location, number, and capacity of the biomass warehouse and biogas facilities. Figure 8 shows the total deviation from the objective functions depending on the biomass of processing capacity, where a stepwise increase is observed.

The third sensitivity analysis addresses the biomass storage capacity parameter. As given in Table 6, biomass processing capacity is varied from −80% to 300%. The economic goal is sensitive to the increase in biomass storage capacity. However, the environmental and social goals remained constant. As shown in Table 6, biomass storage capacity increasing ratio cause changes in the location, number, and capacity of the biomass warehouse and biogas facilities. According to Fig. 9 depending on the changes in the biomass storage capacity, the maximum deviation of the objective functions from the desired values occurs when the capacity is reduced.

The electricity generation capacity is also a crucial parameter. Table 7 shows the effect of electricity generation capacity on the objective functions and the decision variables. While the economic goal is sensitive to the increase in electricity generation capacity, the environmental and social goals remained constant with increasing biomass processing capacity. Table 7 shows no change in facility opening decisions based on electricity generation capacity except for the range −40% and −80%. In addition, Fig. 10 indicates the deviations in electricity generation capacity between −40% and −80% lead to a significant change in the objective function. Also, the parameter affects the decisions on the location, number, and capacity of the biomass warehouses decision.

Lastly, we elaborate on the selected weights of the three goals and their possible reflections on the decision variables. We deploy AHP based on spherical fuzzy sets. The weights of the goals were calculated with the mentioned method, as economic (0.36), environment (0.34), and social (0.30), respectively. Preliminaries of the spherical fuzzy sets, the main stages of the spherical fuzzy AHP method, and the relevant calculations are given in Appendix 1.

We designed six scenarios by deviating the weights as given in Table 8. The analysis shows that changing the weights of the goals does not affect the objective function and decision variables (see Table 8 and Fig. 11).

Table 4 Results of sensitivity analysis on biomass availability

Biomass availability (%)	Economic objective	Environment objective	Social objective	P1	P2	N3	Objective function value	Biomass warehouse	Biogas facility
%10	245,988	179,636	5013	0	135,315	0	135,315	x_{21}, x_{31}, x_{61}	y_{33}
%15	163,013	269,455	7519	0	0	0	102,838	$x_{11}, x_{21}, x_{31}, x_{41}, x_{61}$	y_{23}, y_{41}
%20	438,550	359,273	10,026	3015	151,257	0	154,273	$x_{21}, x_{31}, x_{41}, x_{61}$	y_{13}, y_{33}
%25	315,376	449,092	12,532	0	67,260	0	67,260	$x_{12}, x_{21}, x_{31}, x_{41}, x_{61}$	y_{13}, y_{33}, y_{41}
%30	232,408	541,910	15,039	0	19,216	0	19,216	$x_{12}, x_{22}, x_{31}, x_{41}, x_{51}, x_{61}$	$y_{13}, y_{23}, y_{41}, y_{51}$
%35	−149,351	635,866	17,545	24	128,378	0	128,402	$x_{12}, x_{22}, x_{31}, x_{52}, x_{61}$	y_{13}, y_{23}, y_{53}
%40	226,109	740,361	20,052	1630	80,177	0	81,808	$x_{12}, x_{22}, x_{32}, x_{41}, x_{51}, x_{61}$	$y_{13}, y_{23}, y_{33}, y_{42}$
%45	−83,371	862,596	22,558	8388	52,892	0	61,280	$x_{12}, x_{22}, x_{32}, x_{42}$	$y_{13}, y_{23}, y_{33}, y_{43}$
%50	−99,460	1,048,475	25,065	7081	12,616	0	19,698	$x_{12}, x_{22}, x_{32}, x_{41}, x_{52}, x_{61}$	$y_{13}, y_{23}, y_{33}, y_{41}, y_{53}$
%55	244,390	1,296,757	27,571	120	795	0	915	$x_{12}, x_{22}, x_{32}, x_{42}, x_{52}, x_{61}$	$y_{13}, y_{23}, y_{33}, y_{43}, y_{53}$
%60+	Problem is integer infeasible								

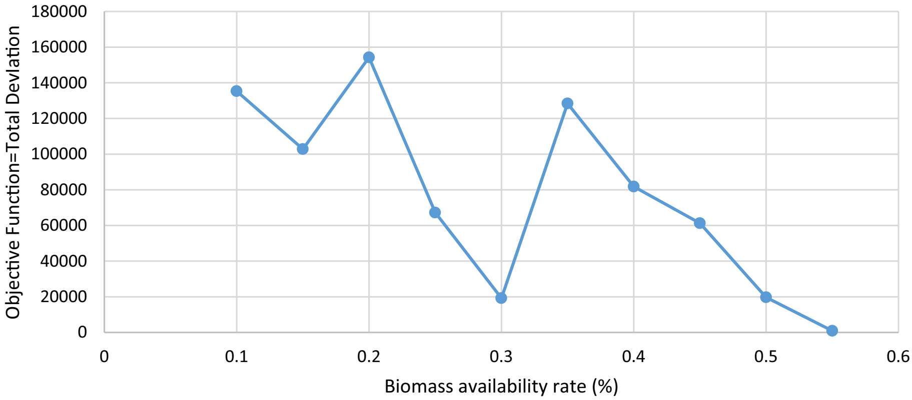

Fig. 7 The effect of biomass amount on the number of facilities and objective function value

6 Policy implications

During the last decade, the biogas industry has grown by 90% (120 GW in 2019 compared to 65 GW in 2010) (Abanades et al., 2022). The results we obtained reveal the potential role of biomass-based sustainable energy in meeting energy needs in Istanbul. Furthermore, the use of wastes, which can become very hazardous due to uncontrolled applications, in producing energy and fertilizers is promising. The study's goals include minimizing environmental impacts and costs, reducing dependency on energy from abroad, and providing energy security. Therefore, the model ensures faster progress on sustainable development goals by increasing renewable energy use in the metropolitan area of Istanbul. In addition, this study presents a real application for the literature on biomass-based sustainable energy supply chain design while revealing the vital role of supply chain management in achieving renewable energy goals. Thus, it provides a novel guideline for local policymakers who are also interested in creating a "green" reputation for the city.

This study can be expanded in different directions. First, a recent study confirms that well-designed policies prosper the biogas market as a renewable energy source (Abanades et al., 2022). National organizations and regulatory bodies play an essential role in developing such markets. The European Biogas Association is a pioneering example of this. Similarly, the Chinese government has made efforts to regulate renewable energy markets, including biogas. In 2019, the waste-free cities initiative by China made a positive contribution to the development of the biogas market (Abanades et al., 2022). Undoubtedly, these examples show us that for the proposed network design to be successful, the issue must be considered from multiple perspectives. Government intervention to promote bioenergy production can be an excellent initial strategy to remedy the negative consequences of greenhouse gas emissions and dependence on carbon-intensive fuels. Thus, the potential effects of various government incentives on the sustainability goals of the network can be investigated. Second, the current study is based on a setting where the biomass is sent to centralized processing facilities. However, small-scale household digesters may be an alternative to this, which is worth evaluating (Rajendran et al., 2012).

This option is particularly attractive in rural areas as it allows biomass to be converted to biogas, where it is produced and consumed on-site. In this way, transportation costs and carbon emissions from transportation will also decrease. This solution will be possible

Table 5 Results of sensitivity analysis on biomass processing capacity

Biomass processing capacity increasing rate	Economic objective	Environment objective	Social objective	P1	P2	N3	Objective function value	Biomass warehouse	Biogas facility
10%	Problem is integer infeasible								
20%	6,089,354	202,771	5013	0	542.35	0	542.35	$x_{13}, x_{23}, x_{33}, x_{41}, x_{53}$	$y_{13}, y_{23}, y_{33}, y_{41}, y_{53}$
30%	3,374,329	181,332	5013	132	27,484	0	27,617	$x_{11}, x_{21}, x_{31}, x_{41}, x_{61}$	y_{13}, y_{23}, y_{43}
40%	2,439,229	179,636	5013	4071	24,761	0	28,833	$x_{11}, x_{21}, x_{31}, x_{41}, x_{61}$	y_{13}, y_{33}, y_{41}
50%	1,811,587	179,636	5013	4034	72,541	0	76,575	$x_{11}, x_{21}, x_{31}, x_{61}$	y_{13}, y_{33}
60%	1,349,068	179,636	5013	1836	81,319	0	83,156	x_{11}, x_{21}, x_{51}	y_{23}, y_{52}
70%	864,503	179,636	5013	0	63,601	0	63,601	$x_{21}, x_{31}, x_{41}, x_{61}$	y_{23}, y_{41}
80%	866,662	179,636	5013	0	63,601	0	63,601	$x_{21}, x_{31}, x_{41}, x_{61}$	y_{23}, y_{41}
90%	253,815	179,636	5013	9841	131,459	0	141,300	$x_{21}, x_{31}, x_{41}, x_{61}$	y_{23}
100%	242,871	179,636	5013	3117	135,315	0	138,432	x_{21}, x_{31}, x_{61}	y_{33}
200%	245,988	179,636	5013	0	135,315	0	135,315	x_{21}, x_{31}, x_{61}	y_{33}
300%	245,988	179,636	5013	0	135,315	0	135,315	x_{21}, x_{31}, x_{61}	y_{33}

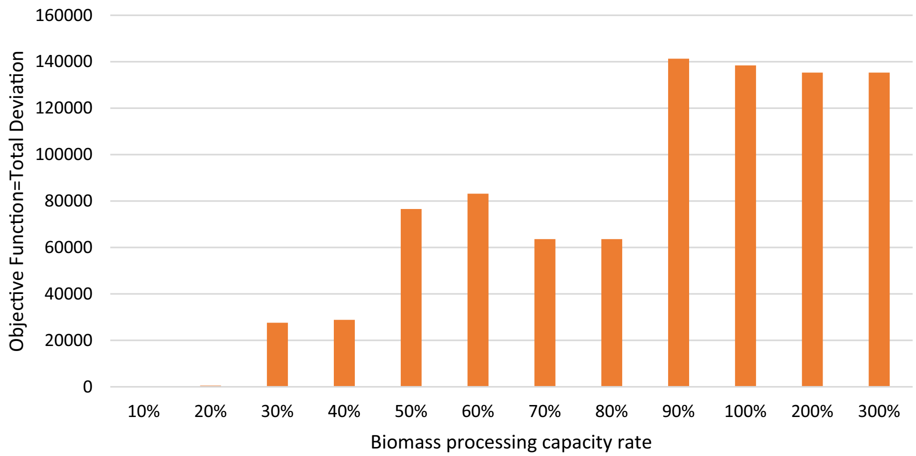

Fig. 8 The effect of biomass processing capacity on the objective function value

by increasing the efficiency of domestic digesters and designing them with cost-effective materials (Rajendran et al., 2012). Third, another important topic is the availability of organic waste. Resources such as food waste, which increase with urbanization, are an important source for biogas production in metropolitan areas such as Istanbul. In addition, another critical source of supply for biomass we foresee in our model is chicken farms. However, closing such businesses for economic or social reasons can threaten the supply network (Raven & Gregersen, 2007).

Furthermore, a trigeneration system can be evaluated to increase supply chain efficiency. Finally, given the current study's results, both annual energy production and utilization of more waste can be achieved by increasing the capacity of biomass warehouses and biogas facilities. Different plant sizes were considered in this study. However, the subject should be studied in more detail, and the optimal facility size should be found by considering energy efficiency (Walla & Schneeberger, 2008).

7 Conclusion

This study presented a model for designing a BS-ESC. A mathematical model was developed that could be used to design and manage this supply chain. The model covered the entire supply chain network from biomass purchase to bioenergy production. It aimed to optimize the whole supply chain network's economic, environmental, and social impacts.

Turkey occupies an important place among the countries in the region in terms of agriculture and livestock. However, the livestock and food industry, which has grown with an increasing human population, has caused a high amount of waste leading to environmental problems. In recent years, poultry and livestock animal-based wastes have been among the issues to be resolved by the policy makers.

Unprocessed waste causes considerable damage to nature and the environment. Simultaneous anaerobic digestion of these wastes is a robust waste disposal method. Recycling of animal wastes and fruit and vegetable (wholesale market) wastes positively contributes to nature in terms of preventing environmental pollution and producing renewable energy and

Table 6 Results of sensitivity analysis on biomass storage capacity

Biomass storage capacity	Economic objective	Environment objective	Social objective	P1	P2	N3	Objective function	X	y
−90%	Problem is integer infeasible								
−80%	291,212	179,636	5013	3,073,517	37,428	0	3,110,945	$x_{12}, x_{21}, x_{41}, x_{51}$	y_{13}, y_{23}, y_{53}
−70%	276,404	179,636	5013	2,166,896	24,760	0	2,191,657	$x_{12}, x_{21}, x_{31}, x_{41}, x_{61}$	y_{13}, y_{33}, y_{41}
−60%	275,510	179,636	5013	1,559,550	103,231	0	1,662,781	x_{12}, x_{21}, x_{41}	y_{13}, y_{23}
−50%	254,641	179,636	5013	13,521	138,433	0	1,184,674	$x_{12}, x_{21}, x_{51}, x_{61}$	y_{23}, y_{52}
−40%	255,605	179,636	5013	615,078	81,884	0	696,963	$x_{12}, x_{21}, x_{31}, x_{41}$	y_{33}, y_{41}
−30%	245,988	179,636	5013	639,629	87,589	0	727,219	x_{12}, x_{21}, x_{31}	y_{11}, y_{23}
−20%	257,658	179,636	5013	0	135,314	0	135,314	x_{21}, x_{31}, x_{61}	y_{33}
−10%	240,736	179,636	5013	5251	135,314	0	140,566	x_{21}, x_{31}, x_{61}	y_{33}
10%	245,425	179,636	5013	2413	137,276	0	139,690	x_{12}, x_{21}, x_{31}	y_{33}
20%	238,852	179,636	5013	4019	143,611	0	147,630	x_{21}, x_{31}	y_{33}
30%	254,507	179,636	5013	0	143,611	0	143,611	x_{21}, x_{31}	y_{33}
40%	254,507	179,636	5013	0	143,611	0	143,611	x_{21}, x_{31}	y_{33}
50%	243,586	179,636	5013	2402	135,314	0	137,716	x_{21}, x_{31}, x_{61}	y_{33}
60%	243,586	179,636	5013	2402	135,314	0	137,716	x_{21}, x_{31}, x_{61}	y_{33}
70%	254,507	179,636	5013	0	143,611	0	143,611	x_{21}, x_{31}	y_{33}
80%	254,507	179,636	5013	0	143,611	0	143,611	x_{21}, x_{31}	y_{33}
90%	247,079	179,636	5013	0	135,314	0	135,314	x_{21}, x_{31}, x_{61}	y_{33}
100%	247,079	179,636	5013	0	135,314	0	135,314	x_{21}, x_{31}, x_{61}	y_{33}
200%	247,079	179,636	5013	0	135,314	0	135,314	x_{21}, x_{31}, x_{61}	y_{33}
300%	338,259	179,636	5013	5,255,487	25,772	0	5,281,259	$x_{12}, x_{21}, x_{31}, x_{41}, x_{51}$	$y_{13}, y_{23}, y_{33}, y_{41}, y_{53}$

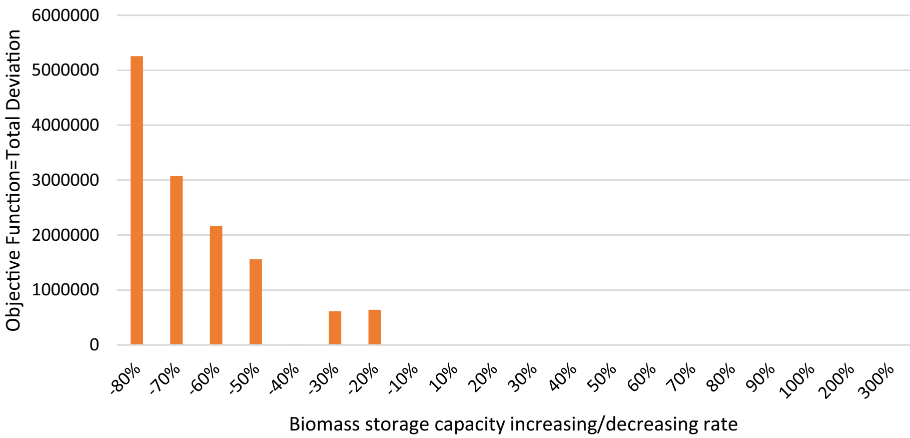

Fig. 9 The effect of biomass storage capacity on the objective function value

organic fertilizers rich in nutrients that are extremely necessary for plants. The electricity generated as a result of processing waste in biogas facilities is guaranteed to be purchased by the government, with incentives aimed at making electricity generation from renewable energy sources widespread. The primary support and incentive mechanism is a fixed price guarantee.

Within the scope of this study, the evaluation of animal and wholesale market wastes in electricity generation from biogas was examined in Istanbul, which has significant waste potential. This study was carried out based on predetermined counties with large amounts of biomass waste. First, the results obtained by using only 10% of wastes were analyzed. When biomass availability was increased, the number of residences using electricity from renewable energy and organic fertilizer production increased linearly. However, analyses could only be performed up to 50% biomass availability due to the low capacity of the biomass warehouses.

This study's main contributions and novelties are as follows: A multi-objective optimization methodology was developed to address strategic and tactical decision-making in a biogas supply chain. The multi-objective goal programming model optimized the triple bottom line of sustainability for the biogas supply chain. The presented model supported food safety by eliminating concerns about using renewable biomass raw materials for energy generation by selecting waste biomass resources for energy production. Furthermore, the study supported view of the circular economy that aims to transform waste into new resources as much as possible by using organic fertilizer. A real-life case in Istanbul Turkey validated the suggested model. Finally, we performed several sensitivity analyses to understand the effects of changes in biomass availability, biomass processing capacity, biomass storage capacity, electricity generation capacity, and the weights of goals, which was done with spherical fuzzy AHP.

Future studies can also focus on developing a more comprehensive geographic model. Secondly, the optimization framework can be extended to a multi-year time horizon. MILP is a widely used approach applied to optimize supply chain decisions among mathematical programming approaches. However, real-world problems are usually more complex; thus, their modeling possesses various uncertainties. Therefore, robust and stochastic programming may be necessary to address the uncertainties, such as biomass availability, indicators

Table 7 Results of sensitivity analysis on electricity generation capacity

Electricity generation capacity	Economic objective	Environment objective	Social objective	P1	P2	N3	Objective function	X	y
−90%	Problem is integer infeasible								
−80%	4,664,090	187,192	5013	2	1153	0	1155	$x_{12}, x_{21}, x_{31}, x_{41}, x_{51}, x_{61}$	$y_{13}, y_{23}, y_{33}, y_{41}, y_{51}$
−70%	2,428,087	181,253	5013	544	26,828	0	27,373	$x_{12}, x_{21}, x_{31}, x_{41}$	y_{13}, y_{33}, y_{41}
−60%	1,834,823	179,636	5013	0	72,539	0	72,539	$x_{12}, x_{21}, x_{31}, x_{61}$	y_{13}, y_{33}, y_{41}
−50%	1,351,803	179,636	5013	3885	74,660	0	78,546	$x_{21}, x_{31}, x_{51}, x_{61}$	y_{23}, y_{52}
−40%	866,662	179,636	5013	0	64,951	0	64,951	$x_{11}, x_{21}, x_{31}, x_{41}$	y_{23}, y_{41}
−30%	257,726	179,636	5013	0	131,482	0	131,482	x_{21}, x_{31}, x_{61}	y_{23}
−20%	245,988	179,636	5013	0	135,314	0	135,314	x_{21}, x_{31}, x_{61}	y_{33}
−10%	245,988	179,636	5013	0	135,314	0	135,314	x_{21}, x_{31}, x_{61}	y_{33}
10%	242,871	179,636	5013	3117	135,314	0	138,432	x_{21}, x_{31}, x_{61}	y_{33}
20%	257,726	179,636	5013	0	131,482	0	131,482	x_{21}, x_{31}, x_{61}	y_{23}
30%	242,871	179,636	5013	3117	135,314	0	138,432	x_{21}, x_{31}, x_{61}	y_{33}
40%	257,726	179,636	5013	0	131,482	0	131,482	x_{21}, x_{31}, x_{61}	y_{23}
50%	242,871	179,636	5013	3117	135,314	0	138,432	x_{21}, x_{31}, x_{61}	y_{33}
60%	242,871	179,636	5013	3117	135,314	0	138,432	x_{21}, x_{31}, x_{61}	y_{33}
70%	242,871	179,636	5013	3117	135,314	0	138,432	x_{21}, x_{31}, x_{61}	y_{33}
80%	257,726	179,636	5013	0	131,482	0	131,482	x_{21}, x_{31}, x_{61}	y_{23}
90%	242,871	179,636	5013	3117	135,314	0	138,432	x_{21}, x_{31}, x_{61}	y_{33}
100%	242,871	179,636	5013	3117	135,314	0	138,432	x_{21}, x_{31}, x_{61}	y_{33}
200%	257,726	179,636	5013	0	131,482	0	131,482	x_{21}, x_{31}, x_{61}	y_{23}
300%	257,726	179,636	5013	0	131,482	0	131,482	x_{21}, x_{31}, x_{61}	y_{23}

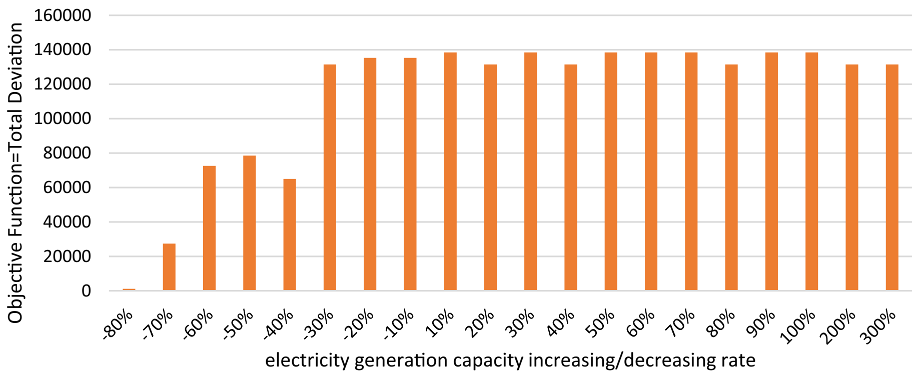

Fig. 10 The effect of electricity generation capacity on the objective function value

Table 8 Results of sensitivity analysis on the weights of goals

	w_1	w_2	w_3	P_1	P_2	P_3	Objective function	x	y
Scenario 1	0.36	0.34	0.30	0	135,315	0	46007.1	x_{21}, x_{31}, x_{61}	y_{33}
Scenario 2	0.34	0.36	0.30	0	135,315	0	48713.4	x_{21}, x_{31}, x_{61}	y_{33}
Scenario 3	0.30	0.34	0.36	0	135,315	0	46007.1	x_{21}, x_{31}, x_{61}	y_{33}
Scenario 4	0.36	0.30	0.34	0	135,315	0	40594.5	x_{21}, x_{31}, x_{61}	y_{33}
Scenario 5	0.30	0.36	0.34	0	135,315	0	48713.4	x_{21}, x_{31}, x_{61}	y_{33}
Scenario 6	0.34	0.30	0.36	0	135,315	0	40594.4	x_{21}, x_{31}, x_{61}	y_{33}

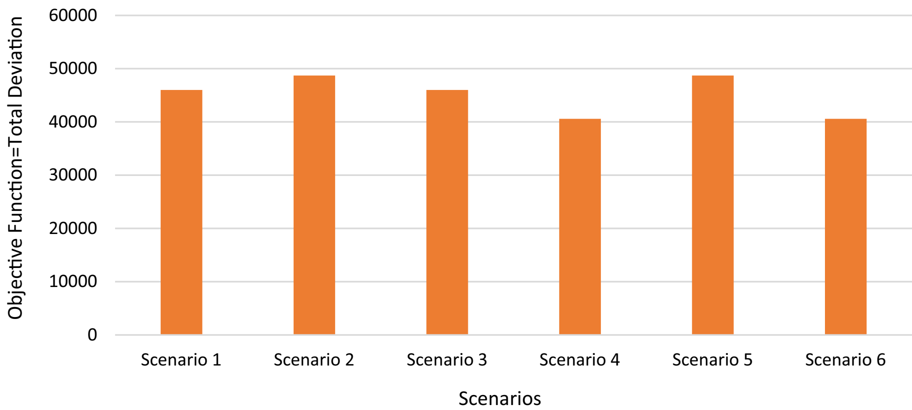

Fig. 11 The effect of the weight of goals on the objective function value

that are applicable to measuring sustainability, product yields, energy prices, and investment costs. Using a single source of biomass or combining different types of biomass can enable an assessment of the effects of biomass use on the supply chain. In the anaerobic digestion of biomass, the impact of different types of digesters on the biomass supply chain can be studied.

Moreover, chemical processes occurring within digesters can be included in the model. In addition to electricity and organic fertilizers, heat can be considered a by-product. The environmental and social impact of replacing organic fertilizer with chemical fertilizer on the supply chain can be examined. The use of liquid fertilizer and heat in digesters can be included in the mathematical model.

The major limitations of this study are as follows. First, the uncertainty is not addressed in this study, which can considerably improve the result of the proposed model. The presented model considers deterministic parameters. Second, the model does not take into account the perishability aspect and transportation losses of biomass feedstocks. This study can be extended to include these aspects in the model. Third, the facility and warehouse locations were chosen as close as possible to the suppliers, considering the transportation costs. Geographical Information Systems and multi-criteria decision methods can be adopted as supportive tools for site selection. Finally, transport costs and emissions are estimated only when the vehicle is full. Costs and emissions should also be included when the vehicle returns empty to make the model realistic.

Appendix 1

Spherical fuzzy sets: preliminaries

Spherical fuzzy sets (SFs) as a generalization of Pythagorean fuzzy sets and neutrosophic sets were presented by Kutlu and Kahraman in 2018. In spherical fuzzy sets, while the squared sum of membership, nonmembership, and hesitancy parameters can be between 0 and 1, each of them can be defined between 0 and 1 independently (Büyüközkan & Güler, 2020; Kutlu Gündoğdu & Kahraman, 2019, 2020). Thus, SFS provides a larger preference domain for decision-makers through the novel concept. For instance, a decision-maker may assign his/her preference for an alternative with respect to a criterion as (0.5, 0.4, 0.6). In this case, the sum of the parameters is larger than one, whereas the squared sum is 0.77. In SFS, the decision-maker should define a hesitancy degree just like other dimensions, with membership and nonmembership degrees.

The basic definitions and notations of the linguistic variable SFS and its operations as follows:

Definition 1 In SFS, $\widetilde{A}_s$ of the universe of discourse U is defined by the following expression;

$$u_{\widetilde{A}_s} : U \rightarrow [0,1], v_{\tilde{A}_s} : U \rightarrow [0,1], \pi_{\tilde{A}_s} : U \rightarrow [0,1]$$

and

$$0 \leq u^2_{\tilde{A}_s}(u) + v^2_{\tilde{A}_s}(u) + \pi^2_{\tilde{A}_s}(u) \leq 1 \quad (u \in U)$$

$$\tilde{A}_s = \left\{ u, \left(u_{\tilde{A}_s}(u), v_{\tilde{A}_s}(u), \pi_{\tilde{A}_s}(u) \right) | u \in U \right\}$$

For each u, the value $u_{\widetilde{A}_s}(u), v_{\widetilde{A}_s}(u)$, and $\pi_{\widetilde{A}_s}(u)$ are the degree of membership, nonmembership, and hesitancy of u to $\widetilde{A}_s$, respectively (Kutlu Gündoğdu & Kahraman, 2020).

Definition 2 Let U_1 and U_2 be two universes. Let $\widetilde{A}_s$ and $\widetilde{B}_s$ be two SFSs of the universe of discourse U_1 and U_2. Geometrical representation of SFS and distances between $\widetilde{A}_s$ and $\widetilde{B}_s$ is given in Fig. 12 (Yang & Chiclana, 2009).

$$D(\tilde{A}_s, \tilde{B}_s) = \frac{2}{\pi}\sum_{i:1}^{n} \arccos\left(1 - 0.5 \times \left[\left(u_{\tilde{A}_s} - u_{\tilde{B}_s}\right)^2 + \left(v_{\tilde{A}_s} - v_{\tilde{B}_s}\right)^2 + \left(\pi_{\tilde{A}_s} - \pi_{\tilde{B}_s}\right)^2\right]\right)$$

$$0 \le D(\tilde{A}_s, \tilde{B}_s) \le n$$

by utilizing $u_{\tilde{A}}^2 + v_{\tilde{A}}^2 + \pi_{\tilde{A}}^2 = 1$, we can find the normalized distances between $\widetilde{A}_s$ and $\tilde{B}_s$ as follows:

$$D_n(\tilde{A}_s, \tilde{B}_s) = \frac{2}{n\pi}\sum_{i:1}^{n} \arccos\left(u_{\tilde{A}_s}(u_i) \times u_{\tilde{B}_s}(u_i) + v_{\tilde{A}_s}(u_i) \times v_{\tilde{B}_s}(u_i) + \pi_{\tilde{A}_s}(u_i) \times \pi_{\tilde{B}_s}(u_i)\right)$$

$$0 \le D_n(\tilde{A}_s, \tilde{B}_s) \le 1$$

Definition 3 The algebraic operations are defined as follows (Kutlu Gündoğdu & Kahraman, 2019).

Addition:

$$\tilde{A}_s \oplus \tilde{B}_s = \left\{ \sqrt{u_{\tilde{A}_s}^2 + u_{\tilde{B}_s}^2 - u_{\tilde{A}_s}^2 \cdot u_{\tilde{B}_s}^2}, v_{\tilde{A}_s}^2 \cdot v_{\tilde{B}_s}^2, \sqrt{\left(\left(1 - u_{\tilde{B}_s}^2\right)\pi_{\tilde{A}_s}^2 + \left(1 - u_{\tilde{A}_s}^2\right)\pi_{\tilde{B}_s}^2 - \pi_{\tilde{A}_s}^2 . \pi_{\tilde{B}_s}^2\right)} \right\}$$

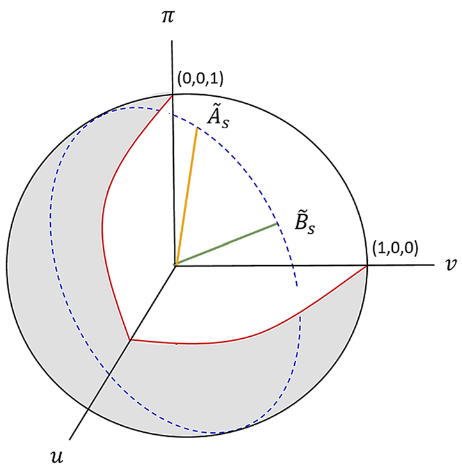

Fig. 12 3D geometrical representation of SFs

Multiplication;

$$\tilde{A}_s \otimes \tilde{B}_s = \left\{ u^2_{\tilde{A}_s} \cdot u^2_{\tilde{B}_s}, \sqrt{v^2_{\tilde{A}_s} + v^2_{\tilde{B}_s} - v^2_{\tilde{A}_s} \cdot v^2_{\tilde{B}_s}}, \sqrt{\left(\left(1 - v^2_{\tilde{B}_s}\right)\pi^2_{\tilde{A}_s} + \left(1 - v^2_{\tilde{A}_s}\right)\pi^2_{\tilde{B}_s} - \pi^2_{\tilde{A}_s}.\pi^2_{\tilde{B}_s}\right)} \right\}$$

Multiplication by a scalar;

$$\tilde{A}_s \otimes x = \left\{ \sqrt{1 - \left(1 - u^2_{\tilde{A}_s}\right)^x}, v^x_{\tilde{A}_s}, \sqrt{\left(1 - u^2_{\tilde{A}_s}\right)^x - \left(1 - u^2_{\tilde{A}_s} - \pi^2_{\tilde{A}_s}\right)^x} \right\}$$

x. Power of $\tilde{A}_s$:

$$\tilde{A}^x_s = \left\{ u^x_{\tilde{A}_s}, \sqrt{1 - \left(1 - v^2_{\tilde{A}_s}\right)^x}, \sqrt{\left(1 - v^2_{\tilde{A}_s}\right)^x - \left(1 - v^2_{\tilde{A}_s} - \pi^2_{\tilde{A}_s}\right)^x} \right\}$$

Union;

$$\tilde{A}_s \cup \tilde{B}_s = \left\{ \max\left(u^2_{\tilde{A}_s}, u^2_{\tilde{B}_s}\right), \min\left(v^2_{\tilde{A}_s} \cdot v^2_{\tilde{B}_s}\right), \min\left(1 - \left(\left(\max\left(u^2_{\tilde{A}_s}, u^2_{\tilde{B}_s}\right)\right)^2 + \left(\min\left(v^2_{\tilde{A}_s}, v^2_{\tilde{B}_s}\right)\right)^2\right), \max\left(\pi^2_{\tilde{A}_s}, \pi^2_{\tilde{B}_s}\right)\right) \right\}$$

Intersection;

$$\tilde{A}_s \cap \tilde{B}_s = \left\{ \min\left(u^2_{\tilde{A}_s}, u^2_{\tilde{B}_s}\right), \max\left(v^2_{\tilde{A}_s} \cdot v^2_{\tilde{B}_s}\right), \min\left(1 - \left(\left(\min\left(u^2_{\tilde{A}_s}, u^2_{\tilde{B}_s}\right)\right)^2 + \left(\max\left(v^2_{\tilde{A}_s}, v^2_{\tilde{B}_s}\right)\right)^2\right), \min\left(\pi^2_{\tilde{A}_s}, \pi^2_{\tilde{B}_s}\right)\right) \right\}$$

Definition 4 The basic operators in SFSs are defined as follows (Kutlu Gündoğdu & Kahraman, 2019).

$$\tilde{A}_s \oplus \tilde{B}_s = \tilde{B}_s \oplus \tilde{A}_s$$

$$\tilde{A}_s \otimes \tilde{B}_s = \tilde{B}_s \otimes \tilde{A}_s$$

$$x\left(\tilde{A}_s \oplus \tilde{B}_s\right) = x \cdot \tilde{A}_s \oplus x \cdot \tilde{B}_s$$

$$x_1 \cdot \tilde{A}_s \oplus x_2 \cdot \tilde{A}_s = \left(x_1 + x_2\right)\tilde{A}_s$$

$$\left(\tilde{A}_s \otimes \tilde{B}_s\right)^x = \tilde{A}^x_s.\tilde{B}^x_s$$

$$\tilde{A}^{-x}_s \otimes \tilde{A}^{-y}_s = \tilde{A}^{-x-y}_s$$

Definition 5 Spherical weighted arithmetic mean (SWAM) with respect to $w = (w_1, w_2, \dots, w_n); \sum_{i:1}^{n} w_i = 1$, is defined as follows (Kutlu Gündoğdu & Kahraman, 2019).

$$\text{SWAM}_w\left(\tilde{A}_{s1}, \tilde{A}_{s2}, \dots, \tilde{A}_{sn}\right) = w_1\tilde{A}_{s1} + w_2\tilde{A}_{s2} + \dots + w_n\tilde{A}_{sn}$$

$$=\left\{\sqrt{1-\prod_{i:1}^{n}\left(1-u_{\widetilde{A}_{si}}^{2}\right)^{w_i}},\prod_{i:1}^{n}v_{\widetilde{A}_{si}}^{w_i},\sqrt{\prod_{i:1}^{n}\left(1-u_{\widetilde{A}_{si}}^{2}\right)^{w_i}-\prod_{i:1}^{n}\left(1-u_{\widetilde{A}_{si}}^{2}-\pi_{\widetilde{A}_{si}}^{2}\right)^{w_i}}\right\}$$

Definition 6 Spherical weighted geometric mean (SWGM) with respect to $w=(w_1,w_2,\dots,w_n); \sum_{i:1}^{n} w_i = 1$ is defined as follows [13]:

$$\mathrm{SWGM}_w\left(\tilde{A}_{s1},\tilde{A}_{s2},\dots,\tilde{A}_{sn}\right)=\tilde{A}_{s1}^{w_1}+\tilde{A}_{s2}^{w_2}+\dots+\tilde{A}_{sn}^{w_n}$$

$$=\left\{\prod_{i:1}^{n}u_{\widetilde{A}_{si}}^{w_i},\sqrt{1-\prod_{i:1}^{n}\left(1-v_{\widetilde{A}_{si}}^{2}\right)^{w_i}},\sqrt{\prod_{i:1}^{n}\left(1-v_{\widetilde{A}_{si}}^{2}\right)^{w_i}-\prod_{i:1}^{n}\left(1-v_{\widetilde{A}_{si}}^{2}-\pi_{\widetilde{A}_{si}}^{2}\right)^{w_i}}\right\}$$

Definition 7 Score functions and accuracy function of sorting SFS are defined with [13];

$\mathrm{Score}\left(\tilde{A}_s\right)=\left(u_{\widetilde{A}_s}-\pi_{\widetilde{A}_s}\right)^2-\left(v_{\widetilde{A}_s}-\pi_{\widetilde{A}_s}\right)^2.$

$\mathrm{Accuracy}\left(\tilde{A}_s\right)=u_{\tilde{A}s}^2+v_{\tilde{A}s}^2+\pi_{\tilde{A}s}^2.$

Note that: $\tilde{A}_s<\tilde{B}_s$ if and only if $\mathrm{Score}\left(\tilde{A}_s\right)<\mathrm{Score}\left(\tilde{B}_s\right)$ or $\mathrm{Score}\left(\tilde{A}_s\right)=\mathrm{Score}\left(\tilde{B}_s\right)$ and $\mathrm{Accuracy}\left(\tilde{A}_s\right)<\mathrm{Accuracy}\left(\tilde{B}_s\right)$.

SF-AHP steps

SF-AHP includes four steps, as given below.

Step 1 Determine criteria weights using SF-AHP.
Step 2 Establish the hierarchical structure of the DMM.
Step 3 Construct a pairwise comparison matrix with spherical fuzzy judgment matrices based on the linguistic terms given in Table 2. Equations (27) and (28) are used to obtain the score indices (SI) in Table 9.

For AMI, VHI, HI, SMI, and EI

$$\mathrm{SI}=\sqrt{\left|100\times\left(\left(u_{\tilde{A}_s}-\pi_{\tilde{A}_s}\right)^2-\left(v_{\tilde{A}_s}-\pi_{\tilde{A}_s}\right)^2\right)\right|} \tag{27}$$

For EI; SLI; LI; VLI; and ALI;

$$\mathrm{SI}^{-1}={}^{1}\Big/\sqrt{\left|100\times\left(\left(u_{\tilde{A}_s}-\pi_{\tilde{A}_s}\right)^2-\left(v_{\tilde{A}_s}-\pi_{\tilde{A}_s}\right)^2\right)\right|} \tag{28}$$

Table 9 Linguistic scale and corresponding SFs (Kutlu Gündoğdu & Kahraman, 2020)

	Score Index (SI)	(u, v, π)
Absolutely more importance (AMI)	9	(0.9,0.1,0.0)
Very high importance (VHI)	7	(0.8,0.2,0.1)
High importance (HI)	5	(0.7,0.3,0.2)
Slightly more importance (SMI)	3	(0.6,0.4,0.3)
Equal importance (EI)	1	(0.5,0.4,0.4)
Slightly low importance (SLI)	1/3	(0.4,0.6,0.3)
Low importance (LI)	1/5	(0.3,0.7,0.2)
Very low importance (VLI)	1/7	(0.2,0.8,0.1)
Absolutely low importance (ALI)	1/9	(0.1,0.9,0.0)

Step 4. Estimate the spherical fuzzy weights of criteria using SWAM operator given in Definition (v). The weighted arithmetic mean is used to compute the spherical fuzzy weights.

Determining the weight of goals by employing SF-AHP

In this stage, SF-AHP determines the relative importance of economic, environmental, and social goal weights.

Step 1 Establish the Hierarchical structure
The hierarchical structure of determining the weights of goals consists of three main criteria, as depicted in Fig. 13.
Step 2 Construct pairwise comparisons matrix
The pairwise comparison matrices for the main criteria are determined by three experts using the linguistic scale in Table 9 (Kutlu Gündoğdu & Kahraman, 2020). The data were collected from three experts through a structured survey. Table 10 gives the experts' opinions on the pairwise matrices of the main criteria.
Aggregated fuzzy pairwise comparison matrix for the main criteria is constructed as per Table 11.

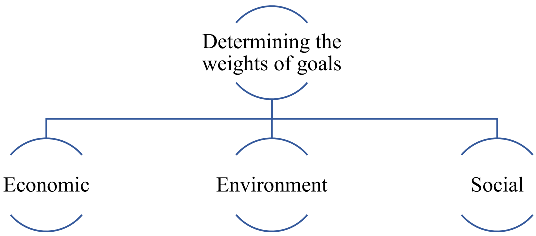

Fig. 13 Hierarchical structure for determining the weights of goals

Table 10 Pairwise matrices for each expert's opinion

		Economic			Environment			Social		
Expert	Criteria	μ	v	π	μ	v	π	μ	v	π
Expert 1	Economic	0.5	0.4	0.4	0.7	0.3	0.2	0.6	0.4	0.3
	Environment	0.3	0.7	0.2	0.5	0.4	0.4	0.4	0.6	0.3
	Social	0.4	0.6	0.3	0.6	0.4	0.3	0.5	0.4	0.4
Expert 2	Environmental	0.5	0.4	0.4	0.4	0.6	0.3	0.6	0.4	0.3
	Economic	0.6	0.4	0.3	0.5	0.4	0.4	0.7	0.3	0.2
	Social	0.4	0.6	0.3	0.3	0.7	0.2	0.5	0.4	0.4
Expert 3	Environmental	0.5	0.4	0.4	0.4	0.6	0.3	0.6	0.4	0.3
	Economic	0.6	0.4	0.3	0.5	0.4	0.4	0.5	0.4	0.4
	Social	0.4	0.6	0.3	0.5	0.5	0.4	0.5	0.4	0.4

Table 11 Aggregated evaluations of three experts on the main criteria

	Economic			Environment			Social		
	μ	v	π	μ	v	π	μ	v	π
Economic	0.50	0.46	0.40	0.48	0.48	0.26	0.60	0.40	0.30
Environment	0.48	0.48	0.26	0.50	0.46	0.40	0.52	0.45	0.29
Social	0.40	0.60	0.30	0.45	0.52	0.29	0.50	0.46	0.40

Table 12 The spherical fuzzy weights of the criteria

	Weights
Economic	0.36
Environment	0.34
Social	0.30

Step 3 Estimate the spherical fuzzy global and local weights of criteria:
We use the SWAM operator given in Definition (v). The weighted arithmetic mean is used to compute the spherical fuzzy weights, as given in Table 12.

Data availability No data were used to support this study.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

Abanades, S., Abbaspour, H., Ahmadi, A., Das, B., Ehyaei, M. A., Esmaeilion, F., & Bani-Hani, E. H. (2022). A critical review of biogas production and usage with legislations framework across the globe. *International Journal of Environmental Science and Technology, 19*(4), 3377–3400. https://doi.org/10.1007/s13762-021-03301-6

Abbasi, G., Khoshalhan, F., & Hosseininezhad, S. J. (2022). Municipal solid waste management and energy production : A multi-objective optimization approach to incineration and biogas waste-to-energy supply chain. *Sustainable Energy Technologies and Assessments, 54*, 102809. https://doi.org/10.1016/j.seta.2022.102809

Aboytes-Ojeda, M., Castillo-villar, K. K., & Eksioglu, S. D. (2022). Modeling and optimization of biomass quality variability for decision support systems in biomass supply chains. *Annals of Operations Research, 314*(2), 319–346. https://doi.org/10.1007/s10479-019-03477-8

Abraham, A., Mathew, A. K., Park, H., Choi, O., & Sindhu, R. (2020). Bioresource technology pretreatment strategies for enhanced biogas production from lignocellulosic biomass. *Bioresource Technology, 301*, 122725. https://doi.org/10.1016/j.biortech.2019.122725

Achinas, S., & Willem Euverink, G. J. (2020). Rambling facets of manure-based biogas production in Europe: A briefing. *Renewable and Sustainable Energy Reviews, 119*, 109566. https://doi.org/10.1016/j.rser.2019.109566

Ahmadvand, S., Khadivi, M., Arora, R., & Sowlati, T. (2021). Energy conversion and management : X Bi-objective optimization of forest-based biomass supply chains for minimization of costs and deviations from safety stock. *Energy Conversion and Management: X, 11*, 100101. https://doi.org/10.1016/j.ecmx.2021.100101

Ahmadvand, S., & Sowlati, T. (2022). A robust optimization model for tactical planning of the forest-based biomass supply chain for syngas production. *Computers & Chemical Engineering, 159*, 107693. https://doi.org/10.1016/j.compchemeng.2022.107693

Akhtari, S., Sowlati, T., Siller-Benitez, D. G., & Roeser, D. (2019). Impact of inventory management on demand fulfilment, cost and emission of forest-based biomass supply chains using simulation modelling. *Biosystems Engineering, 178*, 184–199. https://doi.org/10.1016/j.biosystemseng.2018.11.015

Aksay, M. V., & Tabak, A. (2022). Mapping of biogas potential of animal and agricultural wastes in Turkey. *Biomass Conversion and Biorefinery, 12*(11), 5345–5362.

Allman, A., Lee, C., Martín, M., & Zhang, Q. (2021). Biomass waste-to-energy supply chain optimization with mobile production modules. *Computers & Chemical Engineering, 150*, 107326. https://doi.org/10.1016/j.compchemeng.2021.107326

Amigun, B., & Von Blottnitz, H. (2010). Capacity-cost and location-cost analyses for biogas plants in Africa. *Resources, Conservation and Recycling, 55*(1), 63–73. https://doi.org/10.1016/j.resconrec.2010.07.004

Amore, F., & Bezzo, F. (2016). Strategic optimisation of biomass-based energy supply chains for sustainable mobility. *Computers and Chemical Engineering, 87*, 68–81.

Arabi, M., Yaghoubi, S., & Tajik, J. (2019). Algal biofuel supply chain network design with variable demand under alternative fuel price uncertainty : A case study. *Computers & Chemical Engineering, 130*, 106528. https://doi.org/10.1016/j.compchemeng.2019.106528

Aranguren, M., Castillo-Villar, K. K., & Aboytes-Ojeda, M. (2021). A two-stage stochastic model for co-firing biomass supply chain networks. *Journal of Cleaner Production, 319*, 128582. https://doi.org/10.1016/j.jclepro.2021.128582

Avcioğlu, A. O., & Türker, U. (2012). Status and potential of biogas energy from animal wastes in Turkey. *Renewable and Sustainable Energy Reviews, 16*(3), 1557–1561. https://doi.org/10.1016/j.rser.2011.11.006

Azadeh, A., & Arani, H. V. (2016). Biodiesel supply chain optimization via a hybrid system dynamics-mathematical programming approach. *Renewable Energy, 93*, 383–403. https://doi.org/10.1016/j.renene.2016.02.070

Babazadeh, R., Razmi, J., Pishvaee, M. S., & Rabbani, M. (2017). A sustainable second-generation biodiesel supply chain network design problem under risk. *Omega (united Kingdom), 66*, 258–277. https://doi.org/10.1016/j.omega.2015.12.010

Bairamzadeh, S., Saidi-Mehrabad, M., & Pishvaee, M. S. (2018). Modelling different types of uncertainty in biofuel supply network design and planning: A robust optimization approach. *Renewable Energy, 116*, 500–517. https://doi.org/10.1016/j.renene.2017.09.020

Boro, M., Verma, A. K., Chettri, D., Yata, V. K., & Verma, A. K. (2022). Strategies involved in biofuel production from agro-based lignocellulose biomass. *Environmental Technology and Innovation, 28*, 102679. https://doi.org/10.1016/j.eti.2022.102679

Boulamanti, A. K., Maglio, S. D., Giuntoli, J., & Agostini, A. (2013). Influence of different practices on biogas sustainability. *Biomass and Bioenergy, 53*, 149–161.

Büyüközkan, G., & Güler, M. (2020). Analysis of companies' digital maturity by hesitant fuzzy linguistic MCDM methods. *Journal of Intelligent & Fuzzy Systems, 38*(1), 1119–1132.

Cambero, C., Sowlati, T., & Pavel, M. (2015). Chemical engineering research and design economic and life cycle environmental optimization of forest-based biorefinery supply chains for bioenergy and biofuel production. *Chemical Engineering Research and Design, 107*, 218–235. https://doi.org/10.1016/j.cherd.2015.10.040

Can, A. (2022). Investigation of provincial capacity to produce biogas from waste disposal sites in Turkey. *Energy, 258*, 124778. https://doi.org/10.1016/j.energy.2022.124778

Charnes, A., Cooper, W. W., & Ferguson, R. (1955). Optimal estimation of executive compensation by linear programming. *Management Science, 1*, 138–151.

Charnes, A., & Cooper, W. W. (1961). *Management models and industrial applications of linear programming*. New York: Wiley.

Chen, C. W., & Fan, Y. (2012). Bioethanol supply chain system planning under supply and demand uncertainties. *Transportation Research Part e: Logistics and Transportation Review, 48*(1), 150–164. https://doi.org/10.1016/j.tre.2011.08.004

Chinese, D., Patrizio, P., & Nardin, G. (2014). Effects of changes in Italian bioenergy promotion schemes for agricultural biogas projects: Insights from a regional optimization model. *Energy Policy, 75*, 189–205. https://doi.org/10.1016/j.enpol.2014.09.014

Chyuan, H., & Silitonga, A.S. (2020). Patent landscape review on biodiesel production : Technology updates. *Renewable and Sustainable Energy Reviews*, 118(October 2019), 109526. https://doi.org/10.1016/j.rser.2019.109526

Cobuloglu, H. I., & Büyüktahtakin, I. E. (2014). A mixed-integer optimization model for the economic and environmental analysis of biomass production. *Biomass and Bioenergy, 67*, 8–23. https://doi.org/10.1016/j.biombioe.2014.03.025

Cooper, N., Panteli, A., & Shah, N. (2019). Linear estimators of biomass yield maps for improved biomass supply chain optimisation. *Applied Energy, 253*, 113526. https://doi.org/10.1016/j.apenergy.2019.113526

Corsano, G., Vecchietti, A. R., & Montagna, J. M. (2011). Optimal design for sustainable bioethanol supply chain considering detailed plant performance model. *Computers and Chemical Engineering, 35*(8), 1384–1398. https://doi.org/10.1016/j.compchemeng.2011.01.008

Čuček, L., Lam, H. L., Klemeš, J. J., Varbanov, P. S., & Kravanja, Z. (2010). Synthesis of regional networks for the supply of energy and bioproducts. *Clean Technologies and Environmental Policy, 12*(6), 635–645. https://doi.org/10.1007/s10098-010-0312-6

Čuček, L., Varbanov, P. S., Klemeš, J. J., & Kravanja, Z. (2012). Total footprints-based multi-criteria optimisation of regional biomass energy supply chains. *Energy, 44*(1), 135–145. https://doi.org/10.1016/j.energy.2012.01.040

DECC (Department of Energy & Climate Change), *Government emission conversion factors for greenhouse gas company reporting: Conversion factors* 2017

Díaz-trujillo, L. A., & Fabricio, N. (2019). Optimization of biogas supply chain in Mexico considering economic and environmental aspects. *Renewable Energy, 139*, 1227–1240. https://doi.org/10.1016/j.renene.2019.03.027

Dominique, L., Bambara, F., Sawadogo, M., Roy, D., Blin, J., Anciaux, D., & Koucka, S. (2019). Energy for sustainable development wild and cultivated biomass supply chain for biofuel production. A comparative study in West Africa. *Energy for Sustainable Development, 53*, 1–14. https://doi.org/10.1016/j.esd.2019.08.004

Egieya, J. M., Cu, L., Zirngast, K., Isafiadea, A. J., Pahorc, B., & Kravanja, Z. (2019). Synthesis of biogas supply networks using various biomass and manure types. *Computers and Chemical Engineering, 122*(2019), 129–151.

Elisabeth, L., Büsing, C., & Walther, G. (2018). Robust and sustainable supply chains under market uncertainties and different risk attitudes – A case study of the German biodiesel market. *European Journal of Operational Research, 269*, 302–312. https://doi.org/10.1016/j.ejor.2017.07.015

Fattahi, M., & Govindan, K. (2018). A multi-stage stochastic program for the sustainable design of biofuel supply chain networks under biomass supply uncertainty and disruption risk : A real-life case study. *Transportation Research Part E, 118*, 534–567. https://doi.org/10.1016/j.tre.2018.08.008

Ganesh, R., Torrijos, M., Sousbie, P., Lugardon, A., Steyer, J. P., & Delgenes, J. P. (2015). Effect of increasing proportions of lignocellulosic cosubstrate on the single-phase and two-phase digestion of readily biodegradable substrate. *Biomass and Bioenergy, 80*, 243–251. https://doi.org/10.1016/j.biombioe.2015.05.019

Ganev, E., Ivanov, B., Vaklieva-Bancheva, N., Kirilova, E., & Dzhelil, Y. (2021). A multi-objective approach toward optimal design of sustainable integrated biodiesel/diesel supply chain based on first-and second-generation feedstock with solid waste use. *Energies, 14*(8), 2261.

Gao, M., Wang, D., Wang, H., Wang, X., & Feng, Y. (2019). Biogas potential, utilization and countermeasures in agricultural provinces : A case study of biogas development in Henan Province, China. *Renewable and Sustainable Energy Reviews*, 99(May 2018), 191–200. https://doi.org/10.1016/j.rser.2018.10.005

Ge, Y., Li, L., & Yun, L. (2021). Modeling and economic optimization of cellulosic biofuel supply chain considering multiple conversion pathways. *Applied Energy, 281*, 116059. https://doi.org/10.1016/j.apenergy.2020.116059

Ghaderi, H., Pishvaee, M. S., & Moini, A. (2016). Biomass supply chain network design: An optimization-oriented review and analysis. *Industrial Crops and Products, 94*, 972–1000. https://doi.org/10.1016/j.indcrop.2016.09.027

Ghelichi, Z., Saidi-mehrabad, M., & Pishvaee, M. S. (2018). A stochastic programming approach toward optimal design and planning of an integrated green biodiesel supply chain network under uncertainty : A case study. *Energy, 156*, 661–687. https://doi.org/10.1016/j.energy.2018.05.103

Gital Durmaz, Y., & Bilgen, B. (2020). Multi-objective optimization of sustainable biomass supply chain network design. *Applied Energy, 272*, 115259. https://doi.org/10.1016/j.apenergy.2020.115259

Gonela, V., Zhang, J., & Osmani, A. (2015). Stochastic optimization of sustainable industrial symbiosis based hybrid generation bioethanol supply chains q. *Computers & Industrial Engineering, 87*, 40–65. https://doi.org/10.1016/j.cie.2015.04.025

Guo, C., Hu, H., Wang, S., Rodriguez, L. F., Ting, K. C., & Lin, T. (2022). Multiperiod stochastic programming for biomass supply chain design under spatiotemporal variability of feedstock supply. *Renewable Energy, 186*, 378–393. https://doi.org/10.1016/j.renene.2021.12.144

Habib, M. S., Omair, M., Ramzan, M. B., Chaudhary, T. N., Farooq, M., & Sarkar, B. (2022). A robust possibilistic flexible programming approach toward a resilient and cost-efficient biodiesel supply chain network. *Journal of Cleaner Production, 366*, 132752. https://doi.org/10.1016/j.jclepro.2022.132752

Halim, A., Razik, A., Seong, C., & Elkamel, A. (2019). A model-based approach for biomass-to- bioproducts supply Chain network planning optimization. *Food and Bioproducts Processing, 118*, 293–305. https://doi.org/10.1016/j.fbp.2019.10.001

Han, Y., Wang, L., & Kang, R. (2023). Influence of consumer preference and government subsidy on prefabricated building developer's decision-making: A three-stage game model. *Journal of Civil Engineering and Management*, *29*(1), 35–49.

Han, Y., Yan, X., & Piroozfar, P. (2022). An overall review of research on prefabricated construction supply chain management. *Engineering, Construction and Architectural Management.* https://doi.org/10.1108/ECAM-07-2021-0668

Hosen, M., Siddik, M., Alam, N., Miah, M., & Kabiraj, S. (2022). Biomass energy for sustainable development: evidence from Asian countries. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-022-02850-1

Hosseinalizadeh, R., Khamseh, A. A., & Akhlaghi, M. M. (2019). A multi-objective and multi-period model to design a strategic development program for biodiesel fuels. *Sustainable Energy Technologies and Assessments, 36*, 100545. https://doi.org/10.1016/j.seta.2019.100545

IEA (2020) *Renewables 2020: Analysis and forecast to 2025* https://www.iea.org/reports/renewables-2020. Accessed 1 Dec 2022

IEA (2022) *Renewables 2022: Analysis and forecast to 2027* https://www.iea.org/reports/renewables-2022. Accessed 5 Jan 2023

Jensen, I. G., Münster, M., & Pisinger, D. (2017). Optimizing the supply chain of biomass and biogas for a single plant considering mass and energy losses. *European Journal of Operational Research, 262*(2), 744–758. https://doi.org/10.1016/j.ejor.2017.03.071

Jonker, J. G. G., Junginger, H. M., Verstegen, J. A., Lin, T., Rodríguez, L. F., Ting, K. C., & van der Hilst, F. (2016). Supply chain optimization of sugarcane first generation and eucalyptus second generation ethanol production in Brazil. *Applied Energy, 173*, 494–510. https://doi.org/10.1016/j.apenergy.2016.04.069

Kesharwania, R., Suna, Z., Daglia, C., & Xiong, H. (2019). Moving second generation biofuel manufacturing forward: Investigating economic viability and environmental sustainability considering two strategies for supply chain restructuring. *Applied Energy, 242*(2019), 1467–1496.

Keskin, T., Arslan, K., Karaalp, D., & Azbar, N. (2018). The Determination of the trace element effects on basal medium by using the statistical optimization approach for biogas production from chicken manure. *Waste and Biomass Valorization, 0*, 1–10. https://doi.org/10.1007/s12649-018-0273-2

Kremljak, Z. (2017). *Economy of Biogas Plants*, 0136–0143. https://doi.org/10.2507/28th.daaam.proceedings.018

Kristianto, Y., & Zhu, L. (2019). Platforms planning and process optimization for biofuels supply chain. *Renewable Energy, 140*, 563–579. https://doi.org/10.1016/j.renene.2019.03.072

Kulišić, B., Par, V., & Metzler, R. (2015). Calculation of on-farm biogas potential: A Croatian case study. *Biomass and Bioenergy, 74*, 66–78.

Kutlu Gündoğdu, F., & Kahraman, C. (2019). A novel fuzzy TOPSIS method using emerging interval-valued spherical fuzzy sets. *Engineering Applications of Artificial Intelligence, 85*, 307–323.

Kutlu Gündoğdu, F., & Kahraman, C. (2020). A novel spherical fuzzy analytic hierarchy process and its renewable energy application. *Soft Computing, 24*(6), 4607–4621.

Kwon, O., Kim, J., & Han, J. (2022). Organic waste derived biodiesel supply chain network: Deterministic multi-period planning model. *Applied Energy, 305*, 117847. https://doi.org/10.1016/j.apenergy.2021.117847

Lijó, L., González-García, S., Bacenetti, J., & Moreira, M. T. (2017). The environmental effect of substituting energy crops for food waste as feedstock for biogas production. *Energy, 137*, 1130–1143. https://doi.org/10.1016/j.energy.2017.04.137

Liu, W. Y., Lin, C. C., & Yeh, T. L. (2017). Supply chain optimization of forest biomass electricity and bioethanol coproduction. *Energy, 139*, 630–645. https://doi.org/10.1016/j.energy.2017.08.018

Lyng, K. A., & Brekke, A. (2019). Environmental life cycle assessment of biogas as a fuel for transport compared with alternative fuels. *Energies, 12*(3), 532.

María, M., Chavez, M., Costa, Y., & Sarache, W. (2021). A three-objective stochastic location-inventory-routing model for agricultural waste-based biofuel supply chain. *Computers & Industrial Engineering*, 162(December 2020), 107759.https://doi.org/10.1016/j.cie.2021.107759

Marvin, W. A., Schmidt, L. D., Benjaafar, S., Tiffany, D. G., & Daoutidis, P. (2012). Economic optimization of a lignocellulosic biomass-to-ethanol supply chain. *Chemical Engineering Science, 67*(1), 68–79. https://doi.org/10.1016/j.ces.2011.05.055

Miltner, M., Makaruk, A., & Harasek, M. (2020). Review on available biogas upgrading technologies and innovations towards advanced solutions. *Journal of Cleaner Production, 161*(2017), 1329–1337. https://doi.org/10.1016/j.jclepro.2017.06.045

Miret, C., Chazara, P., Montastruc, L., Negny, S., & Domenech, S. (2016). Design of bioethanol green supply chain: Comparison between first and second generation biomass concerning economic, environmental and social criteria. *Computers and Chemical Engineering, 85*, 16–35. https://doi.org/10.1016/j.compchemeng.2015.10.008

Mirkouei, A., Haapala, K. R., Sessions, J., & Murthy, G. S. (2017). A mixed biomass-based energy supply chain for enhancing economic and environmental sustainability benefits: A multi-criteria decision making framework. *Applied Energy, 206*, 1088–1101. https://doi.org/10.1016/j.apenergy.2017.09.001

Mottaghi, M., Bairamzadeh, S., & Pishvaee, M. S. (2022). A taxonomic review and analysis on biomass supply chain design and planning: New trends, methodologies and applications. *Industrial Crops and Products*, 180(September 2021), 114747. https://doi.org/10.1016/j.indcrop.2022.114747

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

Namany, S., Al-Ansari, T., & Govindan, R. (2019). Optimisation of the energy, water, and food nexus for food security scenarios. *Computers and Chemical Engineering, 129*, 106513. https://doi.org/10.1016/j.compchemeng.2019.106513

Nunes, L.J.R., Causer, T.P., & Ciolkosz, D. (2020). Biomass for energy : A review on supply chain management models. *Renewable and Sustainable Energy Reviews*, 120(April 2019), 109658. https://doi.org/10.1016/j.rser.2019.109658

Ocak, S., & Acar, S. (2021). Biofuels from wastes in Marmara region, Turkey: Potentials and constraints. *Environmental Science and Pollution Research, 28*, 66026–66042.

Osmani, A., & Zhang, J. (2017). Multi-period stochastic optimization of a sustainable multi-feedstock second generation bioethanol supply chain−A logistic case study in Midwestern United States. *Land Use Policy, 61*, 420–450. https://doi.org/10.1016/j.landusepol.2016.10.028

Paolotti, L., Martino, G., Marchini, A., & Boggia, A. (2017). Biomass and bioenergy economic and environmental assessment of agro-energy wood biomass supply chains. *Biomass and Bioenergy, 97*, 172–185. https://doi.org/10.1016/j.biombioe.2016.12.020

Paulo, H., Azcue, X., Barbosa-Póvoa, A. P., & Relvas, S. (2015). Supply chain optimization of residual forestry biomass for bioenergy production: The case study of Portugal. *Biomass and Bioenergy, 83*, 245–256. https://doi.org/10.1016/j.biombioe.2015.09.020

Poeschl, M., Ward, S., & Owende, P. (2010). Prospects for expanded utilization of biogas in Germany. *Renewable and Sustainable Energy Reviews, 14*(7), 1782–1797. https://doi.org/10.1016/j.rser.2010.04.010

Rabbani, M., Saravi, N. A., Farrokhi-Asl, H., Lim, S. F. W. T., & Tahaei, Z. (2018). Developing a sustainable supply chain optimization model for switchgrass-based bioenergy production: A case study. *Journal of Cleaner Production, 200*, 827–843. https://doi.org/10.1016/j.jclepro.2018.07.226

Rajendran, K., Aslanzadeh, S., & Taherzadeh, M. J. (2012). Household biogas digesters—A review. *Energies, 5*(8), 2911–2942. https://doi.org/10.3390/en5082911

Raven, R. P., & Gregersen, K. H. (2007). Biogas plants in Denmark: Successes and setbacks. *Renewable and Sustainable Energy Reviews, 11*(1), 116–132.

Rodr, M. V. (2002). Meta-goal programming. *European Journal of Operational Research, 136*, 422–429.

Sadat, M., Mohseni, S., Hasanzadeh, M., & Saman, M. (2018). Moringa oleifera biomass-to-biodiesel supply chain design : An opportunity to combat deserti fi cation in Iran. *Journal of Cleaner Production, 203*, 313–327. https://doi.org/10.1016/j.jclepro.2018.08.257

Saghaei, M., & Dehghanimadvar, M. (2020). *Optimization and analysis of a bioelectricity generation supply chain under routine and disruptive uncertainty and carbon mitigation policies*, (October 2019), 2976–2999. https://doi.org/10.1002/ese3.716

Salehi, S., Mehrjerdi, Y. Z., Sadegheih, A., & Hosseini-Nasab, H. (2022). Designing a resilient and sustainable biomass supply chain network through the optimization approach under uncertainty and the disruption. *Journal of Cleaner Production, 359*, 131741.

Santibañez-Aguilar, J. E., Lozano-García, D. F., Lozano, F. J., & Flores-Tlacuahuac, A. (2019). Sequential use of geographic information system and mathematical programming for optimal planning for energy production systems from residual biomass. *Industrial & Engineering Chemistry Research, 58*(35), 15818–15837. https://doi.org/10.1021/acs.iecr.9b00492

Santibañez-Aguilar, J. E., Morales-Rodriguez, R., González-Campos, J. B., & Ponce-Ortega, J. M. (2016). Stochastic design of biorefinery supply chains considering economic and environmental objectives. *Journal of Cleaner Production, 136*, 224–245. https://doi.org/10.1016/j.jclepro.2016.03.168

Sarker, B. R., Wu, B., & Paudel, K. P. (2019). Modeling and optimization of a supply chain of renewable biomass and biogas : Processing plant location. *Applied Energy, 239*, 343–355. https://doi.org/10.1016/j.apenergy.2019.01.216

Scano, E. A., Asquer, C., Pistis, A., Ortu, L., Demontis, V., & Cocco, D. (2014). Biogas from anaerobic digestion of fruit and vegetable wastes: Experimental results on pilot-scale and preliminary performance evaluation of a full-scale power plant. *Energy Conversion and Management, 77*, 22–30. https://doi.org/10.1016/j.enconman.2013.09.004

Seyitoglu, S. S., Avcioglu, E., & Haboglu, M. R. (2022). Determination of the biogas potential of animal waste and plant location optimisation: A case study. *International Journal of Energy Research, 46*(14), 20324–20338.

Shabani, N., & Sowlati, T. (2016). A hybrid multi-stage stochastic programming-robust optimization model for maximizing the supply chain of a forest-based biomass power plant considering uncertainties. *Journal of Cleaner Production, 112*, 3285–3293. https://doi.org/10.1016/j.jclepro.2015.09.034

Sharifzadeh, M., Garcia, M. C., & Shah, N. (2015). Biomass and Bioenergy Supply chain network design and operation : Systematic decision- making for centralized, distributed, and mobile biofuel production using mixed integer linear programming (MILP) under uncertainty. *Biomass and Bioenergy, 81*, 401–414. https://doi.org/10.1016/j.biombioe.2015.07.026

Silva, J. O. V., Almeida, M. F., da Conceição Alvim-Ferraz, M., & Dias, J. M. (2018). Integrated production of biodiesel and bioethanol from sweet potato. *Renewable Energy, 124*, 114–120. https://doi.org/10.1016/j.renene.2017.07.052

Singh, P., & Kalamdhad, A. S. (2022). Assessment of agricultural residue-based electricity production from biogas in India: Resource-environment-economic analysis. *Sustainable Energy Technologies and Assessments, 54*, 102843. https://doi.org/10.1016/j.seta.2022.102843

Sözer, S.,& Yaldiz, O. (2011). Muz serası atıkları ve sığır gübresi karışımlarından mezofilik fermantasyon sonucu üretilebilecek biyogaz miktarının belirlenmesi üzerine bir araştırma. A research on determination of biogas production from mixture of banana greenhouse wastes and cattle ma, 24, 75–78 (in Turkish)

Statista, (2022). *Global CO_2 emissions related to energy*, 1975–2021. https://www.statista.com/statistics/526002/energy-related-carbon-dioxide-emissions-worldwide/. Accessed 1 Dec 2022

Tamiz, M., Jones, D., & Romero, C. (1998). Goal programming for decision making: An overview of the current state-of-the-art. *European Journal of Operational Research, 111*(3), 569–581. https://doi.org/10.1016/S0377-2217(97)00317-2

Uddin, R., Shaikh, A. J., Khan, H. R., Shirazi, M. A., Rashid, A., & Qazi, S. A. (2021). Renewable energy perspectives of Pakistan and Turkey: Current analysis and policy recommendations. *Sustainability, 13*(6), 3349. https://doi.org/10.3390/su13063349

Verma, M. K., Shrivastava, R. K., & Tripathi, R. K. (2009). Evaluation of min-max, weighted and preemptive goal programming techniques with reference to mahanadi reservoir project complex. *Water Resources Management, 24*(2), 299–319. https://doi.org/10.1007/s11269-009-9447-9

Walla, C., & Schneeberger, W. (2008). The optimal size for biogas plants. *Biomass and Bioenergy, 32*(6), 551–557.

Wu, J., Zhang, J., Yi, W., Cai, H., Li, Y., & Su, Z. (2022). Agri-biomass supply chain optimization in north China: Model development and application. *Energy, 239*, 122374. https://doi.org/10.1016/j.energy.2021.122374

Yang, Y., & Chiclana, F. (2009). Intuitionistic fuzzy sets: Spherical representation and distances. *International Journal of Intelligent Systems, 24*(4), 399–420.

Yıldız, H. G., & Ayvaz, B. (2018). Waste biomass based energy supply chain network design. *Journal of International Trade, Logistics and Law, 4*(1), 126–137.

Yilmaz Balaman, Ş, & Selim, H. (2015). A decision model for cost effective design of biomass based green energy supply chains. *Bioresource Technology, 191*, 97–109. https://doi.org/10.1016/j.biortech.2015.04.078

Zeren, F., & Akkuş, H. T. (2020). The relationship between renewable energy consumption and trade openness: New evidence from emerging economies. *Renewable Energy, 147*, 322–329. https://doi.org/10.1016/j.renene.2019.09.006

Zhang, C., Xiao, G., Peng, L., Su, H., & Tan, T. (2013). The anaerobic co-digestion of food waste and cattle manure. *Bioresource Technology, 129*, 170–176. https://doi.org/10.1016/j.biortech.2012.10.138

Zhang, T., Wu, X., Shaheen, S. M., Abdelrahman, H., Ali, E. F., Bolan, N. S., & Rinklebe, J. (2022). Improving the humification and phosphorus flow during swine manure composting: A trial for enhancing the beneficial applications of hazardous biowastes. *Journal of Hazardous Materials, 425*, 127906. https://doi.org/10.1016/j.jhazmat.2021.127906

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