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A Robust Possibilistic Bi-Objective Mixed Integer Model for Green Biofuel Supply Chain Design under Uncertain Conditions

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Abstract: In recent years, concerns regarding issues such as climate change, greenhouse gas emissions, fossil reserve dependency, and petroleum price fluctuation have led countries to focus on renewable energies. Meanwhile, in developing countries, designing an appropriate biofuel supply chain network regarding environmental competencies is an important problem. This paper presents a new bi-objective mixed integer mathematical model aiming to minimize CO_2 emission and total costs in the process of the biofuel supply chain, creating a suitable green supply chain network. In this respect, CO_2 emission and biofuel demand are regarded as uncertain data to address the real complex cases. Moreover, the SAUGMECON approach was implemented to construct a single objective model, and the obtained Pareto optimal points were depicted and analyzed. Thereby, a robust possibilistic programming approach was implemented to the proposed model to handle existing imprecise data. Furthermore, the applicability and performance of the proposed model were demonstrated based on an experimental example. In this respect, the obtained results from the proposed robust possibilistic programming model were compared with its crisp form to show the robustness and reliability of the proposed uncertain mathematical model.

Keywords: bi-objective mixed integer programming; renewable energy; green; robust possibilistic approach; biofuel supply chain network design

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1. Introduction

Considering the harmful effects of limited fossil fuel resources on the environment, using renewable energies could play a significant role in the sustainable development of countries. In this respect, utilization of renewable energies, e.g., biofuel, suggests a range of appropriate benefits: boosting regional and local component manufacturing companies, enhancement of regional consultancy and engineering services for using renewable energy, employment creation, decrease in CO_2 emissions, external energies dependence, and impacting electricity transformation to improve service for rural populations [1–3]. Meanwhile, designing the renewable supply chain network (SCN) with regard to environmental competencies might be obtained as an interesting consequence, in which CO_2 emissions have increased at a lower rate than energy utilization, indicating a 5% growth during a specific period [4–6]. However, some authors focused on the renewable SCN design field to solve their problems based on certain data.

Meanwhile, An et al. [7] considered an integrated mathematical approach via strategic and tactical decisions for designing a lignocellulose biofuel supply chain to maximize the profit of the SCN in Central Texas. Bai et al. [8] presented game-theoretic models for biofuel-SCN (BSCN) with feedstock market equilibrium and competitive agricultural land use. Wang et al. [9] considered a renewable identification number system for designing BSCN to provide independent decisions for non-cooperative farms, blenders, and manufacturers. Xie et al. [10] developed a combined approach via a multi-stage and mixed integer mathematical model for designing cellulosic BSCN.

Moreover, Miret et al. [11] extended a multi-objective mixed integer programming (MIP) approach for designing a bioethanol-SCN based on a sustainable development approach. In their study, the extended multi-objective model was refined by the goal programming model rather than the classical epsilon constraint. Bai et al. [12] developed a discretely constrained mathematical program with equilibrium constraints for competitive BSCN. Furthermore, some studies have focused on BSCNs under precise information [13–15].

In many real cases, the uncertainty of renewable-SCN design problems under vague situations is high, in which experts must define their preferences and judgments based on imprecise information and the data is incomplete [16–18]. Indeed, assessing the appropriate results based on deterministic data set is difficult and should be defined under imprecise or uncertain environments [19,20]. To address the issue, some researchers refined their renewable-SCN design with the theories of uncertainty in mind. Thereby, Kim et al. [21] elaborated a two-stage stochastic MIP approach optimizing the design of biomass-SCNs, in which the first and second decisions were capital investment and biomass flows in each scenario, respectively. Cinar et al. [22] assessed the SCN design approaches based on imprecise information. In addition, Yavari and Ajalli [23] proposed a bi-objective mixed-integer linear programming model with the goals of minimizing carbon emissions and total costs to prepare a supplier coalition policy for a green-resilient supply chain network design. Goudarzi et al. [24] tailored a multi-objective, multi-echelon closed-loop supply chain-based robust possibilistic flexible programming method with the aim of minimizing total costs and maximization facility reliability.

Furthermore, Sarkar et al. [25] detailed a flexible and new bioenergy and biofuel production system by transportation disruption considerations under a sustainable supply chain. Zarrinpoor et al. [26] developed a multi-objective switchgrass supply chain network design by considering sustainability concepts and four carbon policies. In this study, the proposed model was refined by the fuzzy interactive programming method and the fuzzy best-worst technique. Zhang et al. [27] tailored an integrated approach based on a mixed-integer linear programming model of geographical information system and sustainability approach to economic optimization of the dual-feedstock lignocellulosic supply chain by soil carbon stock and greenhouse gas emission considerations. Meanwhile, Ghadimi et al. [28] manipulated a new multi-echelon MSW-to-biofuel supply chain network design based on a sustainable cross-efficiency DEA model to find the most suitable location of facilities. Zarei et al. [29] presented a multi-period, multi-feedstocks MIP model to design second- and third-generation BSCN to minimize total costs. Nur et al. [30] manipulated a two-stage stochastic MIP model by considering the biomass quality parameters for the optimal design of the biofuel supply chain. In addition, a parallelized hybrid decomposition algorithm based on the sample average approximation was developed to refine the optimization model.

Moreover, some possibilistic theories or approaches have been prepared to address fuzzy uncertainty, such as fuzzy inference systems [31,32], fuzzy sets theories [33,34], interactive fuzzy approaches [35,36], and robust possibilistic programming methodology [37,38]. Although a wide range of tools is considered to deal with fuzzy environments, the robust possibilistic programming methodology is known as a powerful tool because it can minimize the oscillations of the obtained results through different periods. Consequently, robust possibilistic programming methodology can lead to reliable results with robust features.

However, the renewable-SCN design literature indicates that a few studies focused on multi-objective mathematical models to address their shortcomings. Furthermore, limited attention has been given to the renewable-SCN design based on imprecise information and environmental competencies. In this study, a new bi-objective MIP model was introduced based on environmental competencies to design a suitable green biofuel supply chain network (GBSCN) under uncertain conditions. In this respect, a robust possibilistic programming approach was applied to the proposed imprecise bi-objective MIP model to address uncertainty and assess the robustness of the results. This study focused on representing the robustness of the obtained results from the proposed approach compared with certain conditions. Another point of focus was the structure of biofuel SCN modeling and how a bi-objective mathematical programming model can design an optimal network with environmental competencies.

The rest of this paper is organized as follows: in Section 2, the problem description is expressed. Then, the proposed bi-objective mixed integer mathematical model is presented via assumptions and notations. In Section 3, the solution approach regarding imprecise parameter identification, the robust possibilistic chance constraint programming approach, the e-constraint approach, and software usage are explained. In Section 4, the proposed approach is implemented in a numerical experiment to show the feasibility and efficiency of this study. Finally, conclusions are presented in Section 5.

2. Proposed Model

In this section, a bi-objective MIP model is presented for BGSCN. In this respect, the problem description section explains the BGSCN in detail. Then, the MIP approach is proposed regarding assumptions and mathematical notations.

2.1. Problem Description

Figure 1 represents the BSCN structure, including neighboring farms, farm cooperatives, bio-refinery, blending facilities, and retailers. We examined the green problem from environmental competencies and economic aspects. The biomass was harvested at oil plants, corn and sugar beet farms, and then stored at collection facilities near the farms. The stored biomass was commonly shipped from collection facilities to bio-refineries by trucks to produce different bio-energy types, such as biodiesel, ethanol, and biogas. Meanwhile, the bioenergy, ethanol, was shipped from the bio-refinery to blending facilities to combine the bioenergy with gas. In this respect, the obtained fuel from blending facilities could be considered for all vehicles, e.g., flex-fuel vehicles. As represented in this figure, CO_2 emissions from trucks were considered one of the main concerns for appraising environmental competencies.

Moreover, due to the high supply chain costs, economic issues are addressed in this paper. Therefore, managing the logistics of the BGSC consists of identifying: the (a) amount of biomass transferred between supply chain facilities, (b) location of collection facilities and bio-refineries, (c) amount of biomass *b* processed at bio-refineries, (d) amount of biofuel produced at bio-refineries, and (e) amount of biomass inventory in a facility.

The bi-objective MIP model is proposed to deal with logistical decisions. It is because the mid- and long-term decisions in a BSCN are related and could be impacted by one another. The proposed model utilized mathematical modeling that integrates the location, distribution, and production decisions. Thereby, the main goals of this study were to minimize the total costs of SCN and CO_2 emissions from truck transportation.

To address the issue, the hypotheses considered for developing and refining the proposed bi-objective MIP model were operations research, the SAUGMECON approach [39], and a robust possibilistic programming methodology [40]. In this respect, the operations research approach was considered to establish the bi-objective MIP model by defining all aspects of the considered BSCN problem. Moreover, the SAUGMECON approach was implemented to construct a single objective model, and the obtained Pareto optimal points were depicted and analyzed. Furthermore, a robust possibilistic programming methodology was applied to cope with imprecise and uncertain parameters.

2.2. Assumptions

In this section, some assumptions are provided to reveal the vague aspects of the biofuel supply chain network design; these assumptions were considered through developing the proposed bi-objective MIP model. Therefore, the following assumptions are provided to develop the proposed bi-objective mathematical approach:

- The problem is homogeneous and the number of vehicles is fixed.
- The demand for biofuel and CO_2 emissions during the supply chain are determined as fuzzy parameters.
- The membership functions of fuzzy parameters are determined based on historical data and experts' judgments.
- Backorders are not allowable.
- The capacity of bio-refineries for production and storage is infinite.
- The capacity of collection facilities is supposed to be infinite.

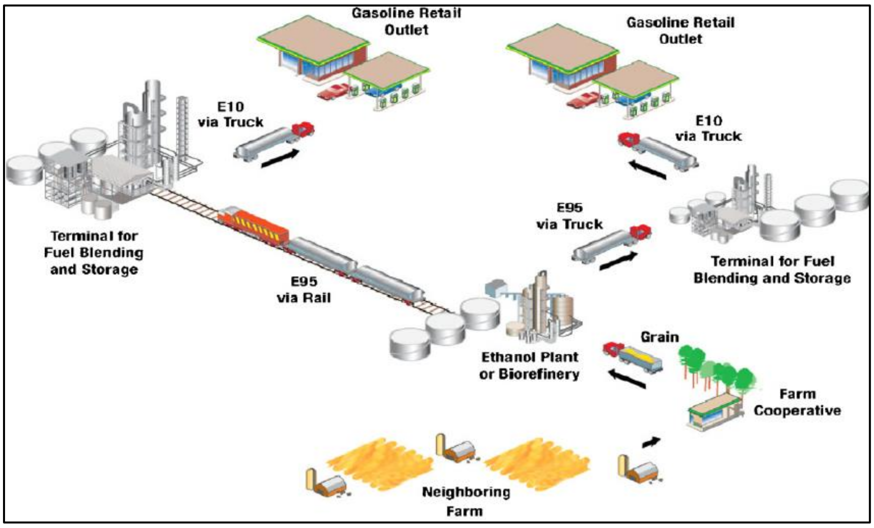

Figure 1. Biofuel supply chain structure (reprinted from [41], with permission from Elsevier).

2.3. Notations

The proposed MIP model is based on the following notations:

Indices

i	Index of bio-refinery location $(i = 1, \ldots, I)$
l	Index of capacity for bio-refinery $(l = 1, \ldots, L)$
b	Index of biomass type $(b = 1, \ldots, B)$
k	Index of harvesting site $(k = 1, \ldots, K)$
j	Index of collection facility $(j = 1, \ldots, J)$
r	Index of blending facility $(r = 1, \ldots, R)$
t	Index of period $(t = 1, \ldots, T)$
f	Index of capacity for collection facility $(f = 1, \ldots F)$

Parameters

$\wp_{il}$	Amortization annul cost of bio-refinery with size of l in location i
p_b	Unit cost of biomass b regarding harvesting, growing and planting
h_b	Holding cost of biomass b
h^e	Holding cost of biofuel e
tc^1_{kj}	Transportation cost of biomass from harvesting site k to collection facility j
tc^2_{ki}	Transportation cost of biomass from harvesting site k to bio-refinery i
tc^3_{ji}	Transportation cost of biomass from collection facility j to bio-refinery i
tc_{ir}	Transportation cost of biofuel from bio-refinery i to blending facility r

$\widetilde{\Im}^1_{kj}$ CO_2 emission rate for transporting of biomass from harvesting site k to collection facility j
$\widetilde{\Im}^2_{ki}$ CO_2 emission rate for transporting of biomass from harvesting site k to bio-refinery i
$\widetilde{\Im}^3_{ji}$ CO_2 emission rate for transporting of biomass from collection facility j to bio-refinery i
$\widetilde{\Im}_{ir}$ CO_2 emission rate for transporting of biofuel from bio-refinery i to blending facility r
$\widetilde{\Im}^p_i$ CO_2 emission rate for producing biofuel at bio-refinery i
ω_b Processing cost of biomass b
λ_{kbt} The quantity of available biomass b at harvesting site k in period t
α_b Conversion rate of biomass b
β Perishability rate
$\widetilde{d}_t$ The quantity of demand in period t
C_l Capacity of bio-refinery for production with size l
S_f Capacity of collection facility for storage with size f
S_l Capacity of bio-refinery for storage with size l

Variables

x_{il} 1 if a bio-refinery with size l is located in site i; 0, otherwise
x_{jf} 1 if a collection facility with size f is located in site j; 0, otherwise
∂_{kbt} The quantity of biomass b harvested at site k in period t
z_{jbt} The quantity of biomass b stored at the collection facility j in period t
z_{ibt} The quantity of biomass b stored at bio-refinery i in period t
z_{it} Mount of biofuel stored at bio-refinery i in period t
y^1_{kjbt} The quantity of biomass b transferred from harvesting site k to collection facility j in period t
y^2_{kibt} The quantity of biomass b transferred from harvesting site k to bio-refinery i in period t
y^3_{jibt} The quantity of biomass b transferred from collection facility j to bio-refinery i in period t
y_{irt} The quantity of biofuel transferred from bio-refinery i to blending facility r in period t
w_{ibt} The quantity of biomass b processed at bio-refinery i in period t
e_{it} The quantity of biofuel produced at bio-refinery i in period t

2.4. Mathematical Model

The bi-objective MIP model was developed for the BGSCN problem as follows:

$$\text{Min}\left\{\begin{array}{l}\sum_{k=1}^{K}\sum_{b=1}^{B}\sum_{t=1}^{T}p_b\partial_{kbt}+\sum_{b=1}^{B}h_b\left(\sum_{t=1}^{T}\left(\sum_{j=1}^{J}z_{jbt}+\sum_{i=1}^{I}z_{ibt}\right)\right)+h^e\sum_{i=1}^{I}\sum_{t=1}^{T}z_{it}\\+\sum_{i=1}^{I}\sum_{b=1}^{B}\sum_{t=1}^{T}\omega_b w_{ibt}+\sum_{b=1}^{B}\sum_{t=1}^{T}\left(\sum_{k=1}^{K}\sum_{j=1}^{J}tc^1_{kj}y^1_{kjbt}+\sum_{k=1}^{K}\sum_{i=1}^{I}tc^2_{ki}y^2_{kibt}+\sum_{j=1}^{J}\sum_{i=1}^{I}tc^3_{ji}y^3_{jibt}\right)\\+\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{r=1}^{R}tc_{ir}y_{irt}+\sum_{i=1}^{I}\sum_{l=1}^{L}\wp_{il}x_{il}\end{array}\right\} \tag{1}$$

$$\text{Min}\left\{\sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{b=1}^{B}\sum_{t=1}^{T}\left(\widetilde{\Im}^1_{kj}y^1_{kjbt}+\widetilde{\Im}^2_{ki}y^2_{kibt}+\widetilde{\Im}^3_{ji}y^3_{jibt}\right)+\sum_{t=1}^{T}\sum_{i=1}^{I}\sum_{r=1}^{R}\widetilde{\Im}_{ir}y_{irt}+\sum_{t=1}^{T}\sum_{i=1}^{I}\widetilde{\Im}^p_i e_{it}\right\} \tag{2}$$

s.t:

$$\partial_{kbt}\le\lambda_{kbt}\quad\forall\, k,t \tag{3}$$

$$\partial_{kbt}\ge\sum_{j=1}^{J}y^1_{kjbt}+\sum_{i=1}^{I}y^2_{kibt}\quad\forall\, k,b,t \tag{4}$$

$$\sum_{k=1}^{K}y^1_{kjbt}+(1-\beta)z_{jb,t-1}=\sum_{i=1}^{I}y^3_{jibt}+z_{jbt}\quad\forall\, j,b,t \tag{5}$$

$$\sum_{k=1}^{K}y^2_{kibt}+\sum_{j=1}^{J}y^3_{jibt}+(1-\beta)z_{ib,t-1}=z_{ibt}+w_{ibt}\quad\forall\, i,b,t \tag{6}$$

$$e_{it}\le\sum_{b=1}^{B}\alpha_b w_{ibt}\quad\forall\, i,t \tag{7}$$

$$z_{i,t-1} + e_{it} = z_{it} + \sum_{r=1}^{R} y_{irt} \quad \forall\, i, t \tag{8}$$

$$\sum_{f=1}^{F} S_f x_{jf} \ \geq \sum_{b=1}^{B} z_{jbt} \quad \forall\, j, t \tag{9}$$

$$\sum_{l=1}^{L} S_l x_{il} \geq \sum_{b=1}^{B} z_{ibt} \quad \forall\, i, t \tag{10}$$

$$\sum_{l=1}^{L} C_l x_{il} \geq e_{it} \quad \forall\, i, t \tag{11}$$

$$\sum_{i=1}^{I} \sum_{r=1}^{R} y_{irt} = \widetilde{d_t} \quad \forall\, t \tag{12}$$

$$\sum_{l=1}^{L} x_{il} \leq 1 \quad \forall\, i \tag{13}$$

$$\sum_{f=1}^{F} x_{jf} \leq 1 \quad \forall\, j \tag{14}$$

$$z_{ib0}, z_{jb0}, z_{i0} = 0 \quad \forall\, i, j, b \tag{15}$$

$$\partial_{kbt}, z_{jbt}, z_{ibt}, z_{it}, y^1_{kjbt}, y^2_{kibt}, y^3_{jibt}, y_{irt}, w_{ibt}, e_{it} \geq 0 \quad \forall\, i, j, b, t, k \tag{16}$$

$$x_{il}, x_{jf} \in \{0, 1\} \quad \forall\, i, j, l, f \tag{17}$$

The first objective function was established to minimize the total cost of the supply chain. The first part of the objective function is planting, growing, and harvesting costs; the second and third parts are related to holding costs; the fourth one is processing costs; the fifth and sixth parts correspond to transportation costs, and the last part is related to amortized costs. Furthermore, the second objective function minimizes total CO_2 emissions in the supply chain regarding biomass transportation and biofuel production.

Constraint (3) indicates that the harvested biomass is limited by the amount of available biomass. Constraint (4) guarantees that the biomass cannot be stored in the harvesting site. Constraints (5) and (6) represent the amount of perishability in stored biomass at the bio-refinery and collection facility, respectively. Constraint (7) indicates the quantity of produced biofuel in each period. In addition, constraint (8) is related to the balance equation. Constraints (9) and (10) are related to the storage capacity of the collection facility and bio-refinery, respectively. Constraint (11) determines the limited capacity of biofuel production for a bio-refinery. Constraint (12) guarantees that the demand for biofuel is to be provided in each period. Constraints (13) and (14) ensure that, at most, one bio-refinery and collection facility can be open at the same place. Constraint (15) represents that the initial inventory level in each facility is zero. Finally, constraints (16) and (17) determine the integer and binary variables, respectively.

3. Solution Approach

In this section, some steps are considered to address the existing shortcomings of the proposed MIP model such as fuzzy uncertainty and multi-objective approach. To address these issues, the following steps were considered for refining the proposed model:

Step 1. Fuzzy parameters identification. Due to the uncertain conditions of real cases, system characteristics, and the lack of experimental data, the optimization of the proposed model is complicated by the imprecise input data. A survey on the biofuel supply chain suggested that the uncertainty of this problem is higher than that of other supply chain topics. Meanwhile, the amount of demand may change in each period; thus, determining the exact value can be difficult or impossible in real biofuel supply chain cases. Furthermore, the CO_2 emission rates for biofuel production, biofuel shipping, and biomass shipping are regarded as uncertain information in the procedure of the proposed approach.

Step 2. Addressing trapezoidal fuzzy parameters. Imprecise information can be handled in various ways. Among them, probability and fuzzy sets (FSs) theories are popular approaches to address incomplete information [42–45]. In this respect, the robust possibilistic programming approach [40] was utilized to decrease the variation of parameters in the biofuel supply chain environment. Therefore, the expected value operator was used to tailor the objective function and necessity measure to consider chance constraints that include imprecise values. Moreover, the trapezoidal possibility membership functions are provided for defining imprecise parameters. In this respect, the primary possibilistic chance constraint programming (BPCCP) approach was manipulated for the compact form of the proposed MIP model below:

$$Min\ E(Z_1) = E(c)x + E(f)y \tag{18}$$

$$Min\ E(Z_2) = E\left(\tilde{d}\right)x \tag{19}$$

$$Nec\left(Rx = \tilde{B}\right) \geq \alpha \tag{20}$$

$$y \in \{0, 1\}, x \geq 0 \tag{21}$$

The necessity measures for the ranges of $t < k$ and $t > k$ are depicted and represented in Figures 2 and 3 [40], respectively. Meanwhile, the necessity measurement equations are represented in Equations (22)–(25).

$$Nec\left(Cx \leq \tilde{R}\right) = 1 - \sup_{t<k}(\mu_R(t)) \tag{22}$$

$$Nec\left(Cx \leq \tilde{R}\right) = \begin{cases} 0 & t \geq R_2 \\ \frac{R_2 - t}{R_2 - R_1} & R_1 \leq t < R_2 \\ 1 & t < R_1 \end{cases} \tag{23}$$

$$Nec\left(\tilde{C}x \leq R\right) = 1 - \sup_{t>k}(\mu_C(t)) \tag{24}$$

$$Nec\left(\tilde{C}x \leq R\right) = \begin{cases} 0 & t < C_3 \\ \frac{t - C_3}{C_4 - C_3} & C_3 \leq t < C_4 \\ 1 & t > C_4 \end{cases} \tag{25}$$

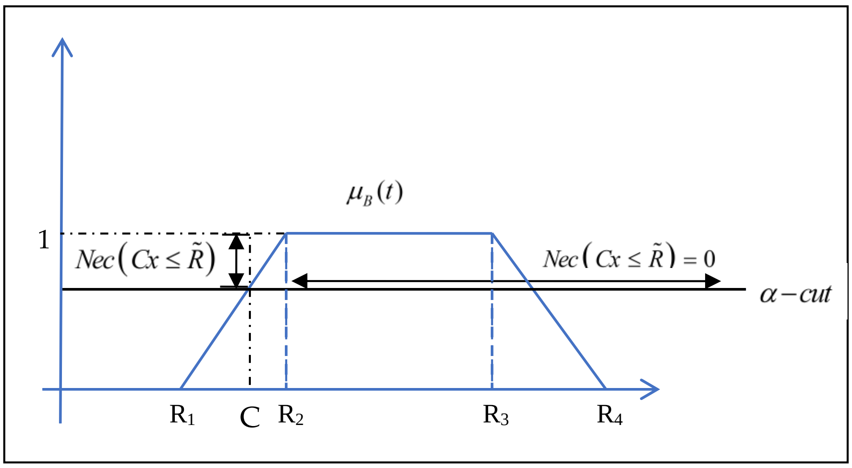

Figure 2. Necessity measure for $t < k$.

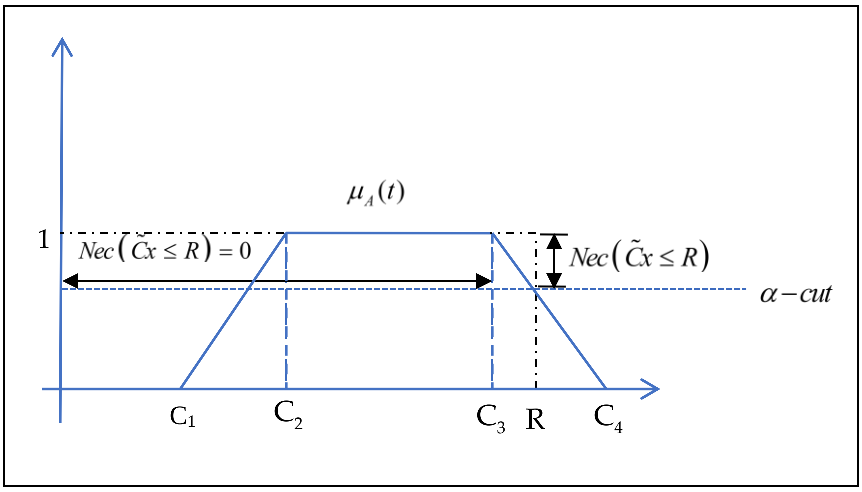

Figure 3. Necessity measure for $t > k$.

The elaborated equivalent crisp mixed integer programming (ECMIP) model is represented below:

$$Min\ E(Z_1) = E(c)x + E(f)y \tag{26}$$

$$Min\ E(Z_2) = E\left(\tilde{d}\right)x \tag{27}$$

$$Rx \le \frac{\alpha}{2}B_{(3)} + \left(1 - \frac{\alpha}{2}\right)B_{(4)} \tag{28}$$

$$Rx \ge \frac{\alpha}{2}B_{(2)} + \left(1 - \frac{\alpha}{2}\right)B_{(1)} \tag{29}$$

$$y \in \{0,1\}, x \ge 0 \tag{30}$$

where the confidence level of chance constraints could be greater than 0.5. The required number of experiments regarding the number of chance constraints for defining appropriate confidence levels may be increased. To address this issue, utilizing robust possibilistic programming (RPP) will be more applicable and reliable. Thereby, the RPP regarding the BPCCP model is provided as:

$$Min\ E(Z_1) = E(c)x + E(f)y \tag{31}$$

$$Min\ \left\{E(Z_2) + \eta(z_{2\max} - z_{2\min}) + \iota\left[B_{(2)} - \left(1 - \frac{\alpha}{2}\right)B_{(1)} - \frac{\alpha}{2}B_{(2)}\right] + \chi\left[\frac{\alpha}{2}B_{(3)} + \left(1 - \frac{\alpha}{2}\right)B_{(4)} - B_{(3)}\right]\right\} \tag{32}$$

$$Rx \le \frac{\alpha}{2}B_{(3)} + \left(1 - \frac{\alpha}{2}\right)B_{(4)} \tag{33}$$

$$Rx \ge \frac{\alpha_4}{2}B_{4(2)} + \left(1 - \frac{\alpha_4}{2}\right)B_{4(1)} \tag{34}$$

$$y \in \{0,1\}, \quad x \ge 0, \quad 0.5 < \alpha \le 1 \tag{35}$$

where the first term of Equation (22) could be the expected value of Z_2 that regards a minimization of the average total outcome of the system. Furthermore, the second term ($\eta(z_{2\max} - z_{2\min})$) ensures optimal robustness for the solution vector by indicating a difference between both possible values of Z_2, which can be defined as follows:

$$z_{2\max} = d_4 x \tag{36}$$

$$z_{2\min} = d_1 x \tag{37}$$

In this respect, η shows the importance of the term regarding the other terms in the objective function. Furthermore, the third and fourth terms represent the feasibility robustness for the solution vector which specifies the confidence level of possibilistic chance constraint, in which possible violation of these constraints is controlled by certain coefficients (i.e., ι and χ).

Step 3. Multi-objective programming approach. The SAUGMECON approach that was introduced by Zhang and Reimann [39] was implemented to construct a single objective model. In this approach, the SAUGMECON method was established using the AUGMECON approach and utilizing the properties of the classical epsilon constraint method [43], which led to an efficient method. In this method, the objectives inequalities are manipulated by the classical epsilon constraint method that is added to the constraint spaces. In addition, the sum of the weighted constraint objectives is considered in the objective function. However, the single objective of the proposed robust possibilistic programming model was determined as follows:

$$Min \left\{ \begin{array}{r} E(Z_2) + \eta(z_{2\max} - z_{2\min}) + \iota\left[B_{(2)} - \left(1 - \frac{\alpha}{2}\right)B_{(1)} - \frac{\alpha}{2}B_{(2)}\right] \\ + \chi\left[\frac{\alpha}{2}B_{(3)} + \left(1 - \frac{\alpha}{2}\right)B_{(4)} - B_{(3)}\right] + \delta\left[\frac{E(c)x + E(f)y}{r_1}\right] \end{array} \right\} \tag{38}$$

$$E(c)x + E(f)y \le \varepsilon_1 \tag{39}$$

$$Rx \le \frac{\alpha}{2}B_{(3)} + \left(1 - \frac{\alpha}{2}\right)B_{(4)} \tag{40}$$

$$Rx \ge \frac{\alpha}{2}B_{(2)} + \left(1 - \frac{\alpha}{2}\right)B_{(1)} \tag{41}$$

$$y \in \{0,1\}, \quad x \ge 0, \quad 0.5 < \alpha \le 1 \tag{42}$$

Step 4. Solve the proposed MIP model. In this respect, the model could be solved by GAMS 24.1 software optimization regarding the CPLEX solver, and all results were obtained on a 3 GHz computer with 4 GB RAM.

4. Numerical Experiment

In this section, a numerical experiment is presented to represent the suitability and applicability of the proposed approach. The proposed robust possibilistic MIP approach for BSCN design was implemented to consider a numerical experiment. In addition, two problems were generated based on input parameters of numerical experiments to indicate the validity of the proposed approach. Furthermore, the obtained results from a robust possibilistic approach were compared with the crisp form of the proposed approach to show the feasibility and efficiency of the presented approach.

4.1. Outlined of Numerical Experiment

The BSCN was established based on three bio-refinery locations, two types of capacities for bio-refinery, one feedstock biomass, two harvesting sites, three collection facilities, two blending facilities, and three types of capacities for collection facilities in three periods. Thereby, the input data were collected based on experts' judgments and field studies. For instance, the main parameters which were considered possibilistic information are defined in Table 1.

Table 1. Defining the fuzzy values for uncertain parameters.

Parameters	Fuzzy Numbers Values
$\widetilde{d}_t$	$(U[120,280], U[140,310], U[160,340], U[190,380])$
$\widetilde{\Im}^1_{kj}$	$(U[1.2,1.7], U[1.3,1.8], U[1.35,1.9], U[1.4,2])$
$\widetilde{\Im}^2_{ki}$	$(U[2.2,3], U[2.4,3.15], U[2.6,3.3], U[2.8,3.5])$
$\widetilde{\Im}^3_{ji}$	$(U[0.1,0.6], U[0.2,0.7], U[0.3,0.8], U[0.4,0.9])$
$\widetilde{\Im}_{ir}$	$(U[1.1,1.6], U[1.2,1.7], U[1.3,1.8], U[1.4,1.9])$
$\widetilde{\Im}^p_i$	$(U[2.1,2.9], U[3.1,3.5], U[3.6,4], U[4.1,4.6])$

As indicated in Table 1, the amount of demand in each period and CO_2 emissions during the biofuel production in the supply chain are followed by the uniform fuzzy numbers.

4.2. Implementation and Results

The proposed robust possibilistic MIP approach was applied based on the aforementioned input parameters. In this respect, the well-known SAUGMECON method was implemented to take into account the bi-objective nature of the presented model. Notably, this method could provide an appropriate approximation of the Pareto optimal points for the decision makers. Meanwhile, the obtained Pareto optimal points are depicted in Figure 4 concerning the Pareto frontier points from the payoff table and minimizing both objective functions.

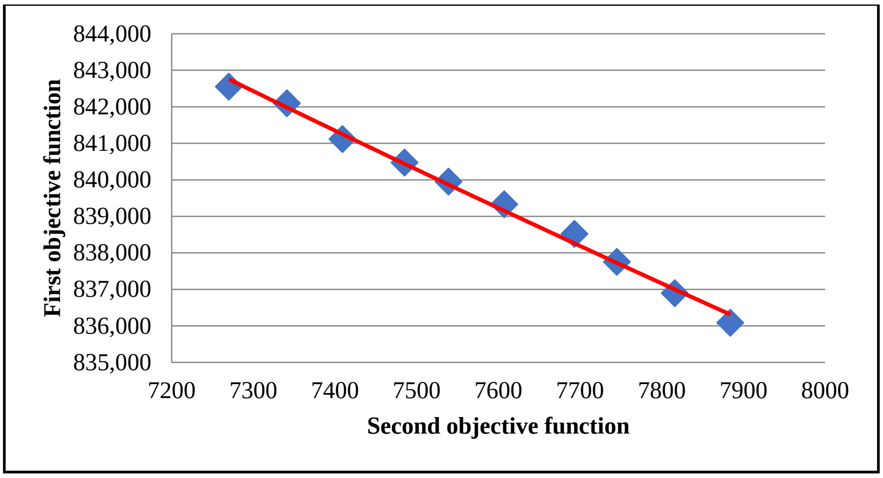

Figure 4. Pareto optimal points and the conflict of objective functions.

The obtained Pareto optimal points could be sent to decision makers for discussion. In this respect, the results show that one site for biomass harvesting was considered. Nearly 450 units were harvested in the first period, and 367 and 198 units were harvested in the second and third periods, respectively. Among the three collection facilities, the third one was opened, and the harvested biomass in each period was shipped to it. Moreover, the third candidate from three bio-refinery locations was selected to produce the biofuel. Notably, the harvested biomass was shipped from the collection facility to the third bio-refinery with a capacity of 300 units per period. Furthermore, the bio-refinery produced 287.5, 235, and 126 biofuel units in three periods, respectively, for covering the amount of biofuel demand. It is worthwhile to note that the model determined that the storage of biomass and biofuel did not occur during the BSCN.

4.3. Verification Procedures

In this section, numerical examples are defined based on the prepared numerical experiment in Section 4.1. In this manner, the generated numerical examples are provided by simulating the input parameters based on the defined parameters in Table 1. However, two simulated problems were solved based on a bi-objective robust possibilistic MIP model. The obtained results are reported for the main variables in Figures 5–7. In this respect, the objective function values and Pareto optimal points for both problems are depicted in Figure 5. As represented in this figure, the trend of the objective function values is the same and confirms the scale ranges of the main numerical experiment.

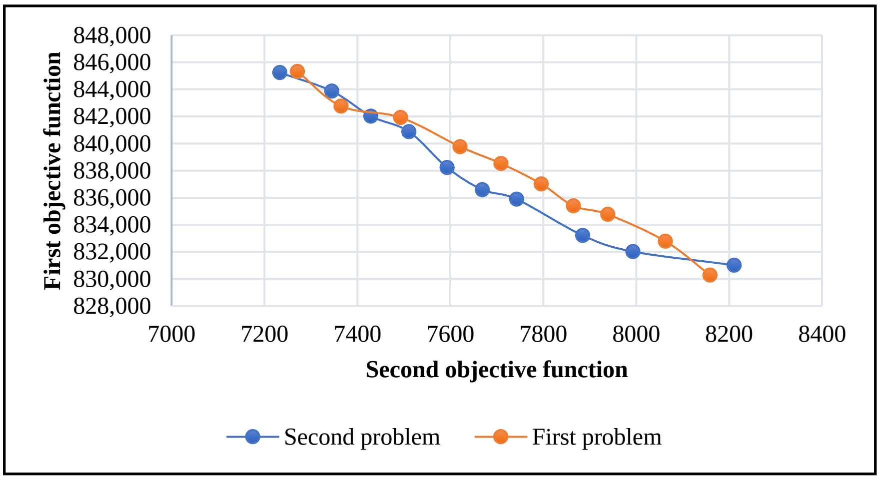

Figure 5. Pareto optimal points and the conflict of objective functions.

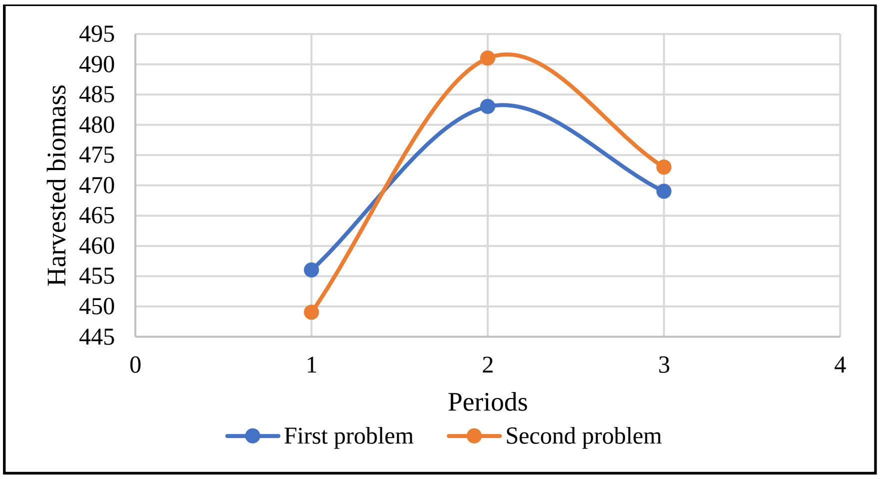

Figure 6. The amount of harvested biomass for both generated problems.

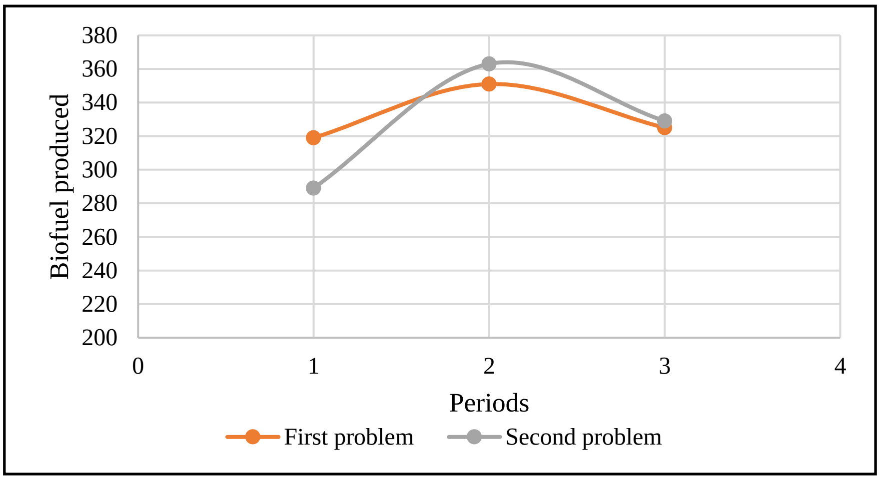

Figure 7. The amount of produced biofuel for both generated problems.

The quantity of harvested biomass in each period ($\sum_{k=1}^{K} \sum_{b=1}^{B} \partial_{kbt}$) is depicted for both considered problems in Figure 6.

The quantity of produced biofuel in all bio-refineries ($\sum_{i=1}^{I} e_{it}$) is reported in Figure 7 for both generated problems.

Consequently, the obtained results for both generated problems indicate that the proposed bi-objective robust possibilistic MIP model can lead to reliable results. Moreover, the objective function values as Pareto optimal points for both generated problems are confirmed by the obtained results from the main numerical experiment.

4.4. Comparative Analysis

Results from the proposed robust possibilistic MIP model were compared with the crisp form of this model to represent the efficiency and robustness of the proposed approach. In this respect, the obtained Pareto optimal points from the RPP model and the crisp form of the proposed model are depicted in Figure 8. The proposed robust possibilistic MIP model provided a wide range of Pareto optimal points regarding a lower dispersion than the crisp form of the proposed model. Indeed, the dispersion of Pareto optimal points was calculated based on a standard deviation measure to indicate the robustness of the proposed RPP model. Furthermore, averaging the computation of Pareto optimal points' values for the first and second objective functions demonstrates that the proposed RPP model leads to lower total costs and CO_2 emission versus the crisp form. In this respect, the results show that the proposed RPP model versus the crisp form of the proposed approach could improve the first and second objective functions by 20.8% and 6.2%, respectively.

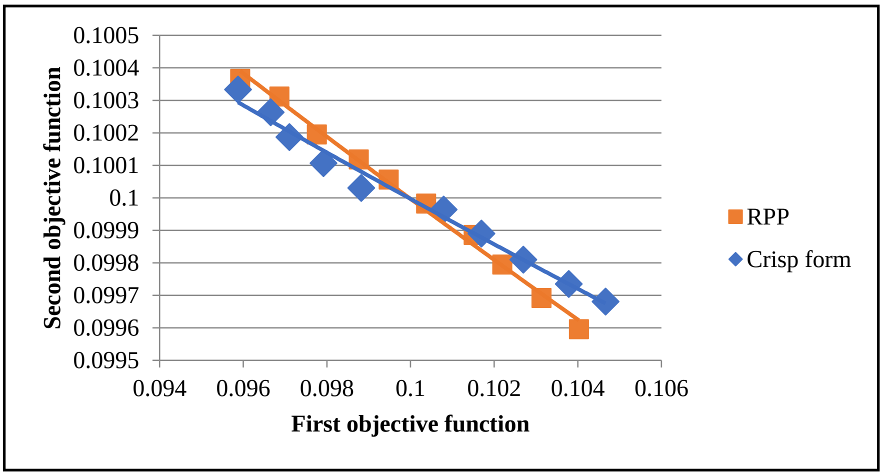

Figure 8. Pareto optimal points of RPP versus the crisp form of the proposed model.

In addition, to represent the efficiency and robustness of the proposed RPP approach, the dispersion concept was considered and determined based on a standard deviation measure for outputs of the proposed RPP model and the crisp form of the proposed model. Meanwhile, the results are represented in Table 2. Assessed outcomes from the proposed RPP approach demonstrate that they have lower dispersion than the obtained results from the crisp form of the proposed approach. Consequently, the assessed results from the proposed RPP model are robust regarding the system environment changes.

Table 2. Comparative analysis for the proposed RPP model and crisp form of the model.

Periods	Proposed RPP Model		Crisp Form of Proposed Model	
	∂_{kbt}	e_{it}	∂_{kbt}	e_{it}
t = 1	450	287.5	547	350
t = 2	367	235	453	290
t = 3	198	126	281	180
Standard deviation measure	128.4	82.3	134.9	86.2

As demonstrated in Table 2, the proposed RPP model could improve the dispersion of harvested biomass (∂_{kbt}) by 4.9% and the biofuel produced at bio-refinery (e_{it}) by 4.5% versus the crisp form of the proposed model. Therefore, it is concluded that the obtained results from the proposed RPP model are more reliable than the crisp form of the proposed model.

The goals of this study to minimize total costs as well as CO_2 emission regarding appropriate BSCN design were achieved. Therefore, a schematic representation of the BSCN design regarding the obtained results from the proposed RPP approach and the crisp form of the proposed model can be useful. The aforementioned explanations are provided in Figure 9. In this case, both the proposed RPP approach and the crisp form of the proposed model considered a specified bio-refinery, but they selected different facilities for BSCN design.

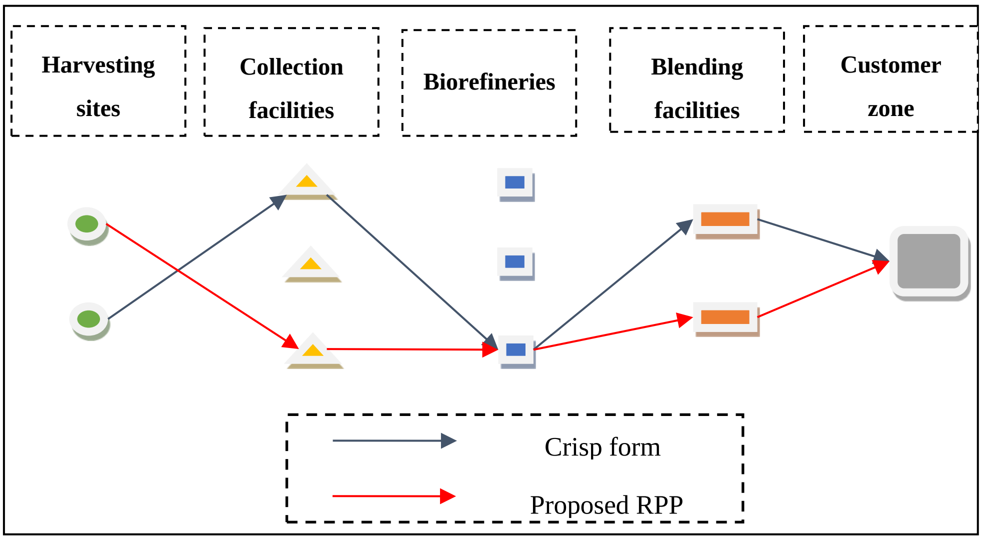

Figure 9. Biofuel supply chain network design based on the proposed RPP approach and crisp form of the proposed model.

5. Conclusions and Future Directions

One of the main issues that must be mentioned currently is human dependence on nonrenewable energies which leads to producing more greenhouse gas. It is necessary to consider renewable energies as biofuel regarding the environmental competencies to decrease greenhouse gas emissions. In this respect, the goals of this study were to simultaneously minimize the total costs and CO_2 emissions for the biofuel green supply chain network (BGSCN). To address the issue, a new mixed integer programming (MIP) model for designing the BGSCN was proposed. In this case, the biofuel demand and the CO_2 emission parameters were recognized as imprecise fuzzy information which should be considered in the proposed model for ensuring real-life requirements. Meanwhile, the robust possibilistic approach was considered to deal with existing uncertainty. Therefore, the robust possibilistic MIP model was elaborated for BGSCN design. Moreover, a numerical example was provided to represent the performance and capability of the proposed approach. In addition, two problems are generated based on numerical experiments to assess the validation of the proposed approach. In this sake, the obtained results indicate that the proposed approach can lead to reliable results, and also the obtained Pareto optimal points for both aforementioned problems confirmed the objective function values scales of the main numerical experiment. Then, the proposed RPP model was compared with the crisp form of the proposed model regarding the obtained results from both approaches. The comparative analysis demonstrated that the presented RPP approach versus the crisp form of the model could improve the first and second objective functions by 20.8% and 6.2%, respectively. Furthermore, 4.9% and 4.5% improvements were obtained for the harvested biomass and biofuel produced at bio-refinery variables, respectively. Consequently, the proposed RPP model had better performance than the crisp form of the proposed model. Meanwhile, the main limitation of this study was that the proposed approach of this study could not solve large-sized problems. On the other hand, another weakness of the proposed bi-objective robust possibilistic MIP model is its high computational complexity.

To address these issues, developing algorithms to solve large-sized problems and extending a decision-support system to manage computational complexity can be considered for future directions. Moreover, considering more parameters based on imprecise information is an exciting issue. Furthermore, providing sustainability concepts by considering the social objective function for the proposed MIP model is an interesting topic for future research.

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References

1. Gitinavard, H.; Akbarpour Shirazi, M.; Fazel Zarandi, M.H. A possibilistic programming approach for biomass supply chain network design under hesitant fuzzy membership function estimation. *Sci. Iran.* **2021**. Available online: http://scientiairanica.sharif.edu/article_22588.html (accessed on 18 September 2022). [CrossRef]
2. Gitinavard, H.; Ghaderi, H.; Pishvaee, M.S. Green supplier evaluation in manufacturing systems: A novel interval-valued hesitant fuzzy group outranking approach. *Soft Comput.* **2018**, *22*, 6441–6460. [CrossRef]
3. Salimian, S.; Mousavi, S.M. A new scenario-based robust optimization approach for organ transplantation network design with queue condition and blood compatibility under climate change. *J. Comput. Sci.* **2022**, *62*, 101742. [CrossRef]
4. Gitinavard, H.; Shirazi, M.A.; Zarandi, M.H.F. Sustainable feedstocks selection and renewable products allocation: A new hybrid adaptive utility-based consensus model. *J. Environ. Manag.* **2020**, *264*, 110428. [CrossRef] [PubMed]
5. Zolfaghari, S.; Mousavi, S.M. A novel mathematical programming model for multi-mode project portfolio selection and scheduling with flexible resources and due dates under interval-valued fuzzy random uncertainty. *Expert Syst. Appl.* **2021**, *182*, 115207. [CrossRef]
6. Vahdani, B.; Veysmoradi, D.; Mousavi, S.; Amiri, M. Planning for relief distribution, victim evacuation, redistricting and service sharing under uncertainty. *Socio-Econ. Plan. Sci.* **2022**, *80*, 101158. [CrossRef]
7. An, H.; Wilhelm, W.E.; Searcy, S.W. A mathematical model to design a lignocellulosic biofuel supply chain system with a case study based on a region in Central Texas. *Bioresour. Technol.* **2011**, *102*, 7860–7870. [CrossRef]
8. Bai, Y.; Ouyang, Y.; Pang, J.-S. Biofuel supply chain design under competitive agricultural land use and feedstock market equilibrium. *Energy Econ.* **2012**, *34*, 1623–1633. [CrossRef]
9. Wang, X.; Ouyang, Y.; Yang, H.; Bai, Y. Optimal biofuel supply chain design under consumption mandates with renewable identification numbers. *Transp. Res. Part B Methodol.* **2013**, *57*, 158–171. [CrossRef]
10. Xie, F.; Huang, Y.; Eksioglu, S. Integrating multimodal transport into cellulosic biofuel supply chain design under feedstock seasonality with a case study based on California. *Bioresour. Technol.* **2014**, *152*, 15–23. [CrossRef]

11. Miret, C.; Chazara, P.; Montastruc, L.; Negny, S.; Domenech, S. Design of bioethanol green supply chain: Comparison between first and second generation biomass concerning economic, environmental and social criteria. *Comput. Chem. Eng.* **2016**, *85*, 16–35. [CrossRef]
12. Bai, Y.; Ouyang, Y.; Pang, J.-S. Enhanced models and improved solution for competitive biofuel supply chain design under land use constraints. *Eur. J. Oper. Res.* **2016**, *249*, 281–297. [CrossRef]
13. Vakili, R.; Akbarpour Shirazi, M.; Gitinavard, H. Multi-echelon green open-location-routing problem: A robust-based stochastic optimization approach. *Sci. Iran.* **2021**, *28*, 985–1000. [CrossRef]
14. Gitinavard, H.; Ghodsypour, S.H.; Akbarpour Shirazi, M. A bi-objective multi-echelon supply chain model with Pareto optimal points evaluation for perishable products under uncertainty. *Sci. Iran.* **2019**, *26*, 2952–2970. [CrossRef]
15. Ghaderi, H.; Gitinavard, H.; Pishvaee, M.S. A system dynamics approach to analysing bioethanol and biodiesel supply chains: Increasing bioethanol and biodiesel market shares in the USA. *Int. J. Energy Technol. Policy* **2020**, *16*, 57–84. [CrossRef]
16. Salimian, S.; Mousavi, S.M. A robust possibilistic optimization model for organ transplantation network design considering climate change and organ quality. *J. Ambient Intell. Humaniz. Comput.* **2022**, 1–24. Available online: https://link.springer.com/article/10.1007/s12652-022-03863-4 (accessed on 18 September 2022). [CrossRef]
17. Foroozesh, N.; Karimi, B.; Mousavi, S. Green-resilient supply chain network design for perishable products considering route risk and horizontal collaboration under robust interval-valued type-2 fuzzy uncertainty: A case study in food industry. *J. Environ. Manag.* **2022**, *307*, 114470. [CrossRef]
18. Mahdavi-Roshan, P.; Mousavi, S.M. A new interval-valued fuzzy multi-objective approach for project time–cost–quality trade-off problem with activity crashing and overlapping under uncertainty. *Kybernetes* **2022**. *ahead-of-print*. [CrossRef]
19. Gitinavard, H. Strategic evaluation of sustainable projects based on hybrid group decision analysis with incomplete information. *J. Qual. Eng. Prod. Optim.* **2019**, *4*, 17–30.
20. Gitinavard, H.; Makui, A.; Jabbarzadeh, A. Interval-valued hesitant fuzzy method based on group decision analysis for estimating weights of decision makers. *J. Ind. Syst. Eng.* **2016**, *9*, 96–110.
21. Kim, J.; Realff, M.J.; Lee, J.H. Optimal design and global sensitivity analysis of biomass supply chain networks for biofuels under uncertainty. *Comput. Chem. Eng.* **2011**, *35*, 1738–1751. [CrossRef]
22. Cinar, D.; Pardalos, P.M.; Rebennack, S. Evaluating Supply Chain Design Models for the Integration of Biomass Co-firing in Existing Coal Plants Under Uncertainty. In *Handbook of Bioenergy*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 191–217.
23. Yavari, M.; Ajalli, P. Suppliers' coalition strategy for green-Resilient supply chain network design. *J. Ind. Prod. Eng.* **2021**, *38*, 197–212. [CrossRef]
24. Goudarzi, Z.; Seifbarghy, M.; Pishva, D. Bi-objective modeling of a closed-loop multistage supply chain considering the joint assembly center and reliability of the whole chain. *J. Ind. Prod. Eng.* **2022**, *39*, 230–252. [CrossRef]
25. Sarkar, B.; Mridha, B.; Pareek, S.; Sarkar, M.; Thangavelu, L. A flexible biofuel and bioenergy production system with transportation disruption under a sustainable supply chain network. *J. Clean. Prod.* **2021**, *317*, 128079. [CrossRef]
26. Zarrinpoor, N.; Khani, A. Designing a sustainable biofuel supply chain by considering carbon policies: A case study in Iran. *Energy Sustain. Soc.* **2021**, *11*, 38. [CrossRef]
27. Zhang, B.; Guo, C.; Lin, T.; Faaij, A.P.C. Economic optimization for a dual-feedstock lignocellulosic-based sustainable biofuel supply chain considering greenhouse gas emission and soil carbon stock. *Biofuels Bioprod. Biorefining* **2022**, *16*, 653–670. [CrossRef]
28. Ghadami, M.; Sahebi, H.; Pishvaee, M.; Gilani, H. A sustainable cross-efficiency DEA model for international MSW-to-biofuel supply chain design. *RAIRO-Oper. Res.* **2021**, *55*, S2653–S2675. [CrossRef]
29. Zarei, M.; Niaz, H.; Dickson, R.; Ryu, J.-H.; Liu, J.J. Optimal design of the biofuel supply chain utilizing multiple feedstocks: A Korean case study. *ACS Sustain. Chem. Eng.* **2021**, *9*, 14690–14703. [CrossRef]
30. Nur, F.; Aboytes-Ojeda, M.; Castillo-Villar, K.K.; Marufuzzaman, M. A two-stage stochastic programming model for biofuel supply chain network design with biomass quality implications. *IISE Trans.* **2021**, *53*, 845–868. [CrossRef]
31. Pourjavad, E.; Shahin, A. The application of Mamdani fuzzy inference system in evaluating green supply chain management performance. *Int. J. Fuzzy Syst.* **2018**, *20*, 901–912. [CrossRef]
32. Lima-Junior, F.R.; Carpinetti, L.C.R. An adaptive network-based fuzzy inference system to supply chain performance evaluation based on SCOR® metrics. *Comput. Ind. Eng.* **2020**, *139*, 106191. [CrossRef]
33. Stekelorum, R.; Laguir, I.; Gupta, S.; Kumar, S. Green supply chain management practices and third-party logistics providers' performances: A fuzzy-set approach. *Int. J. Prod. Econ.* **2021**, *235*, 108093. [CrossRef]
34. Coppolino, L.; Romano, L.; Scaletti, A.; Sgaglione, L. Fuzzy set theory-based comparative evaluation of cloud service offerings: An agro-food supply chain case study. *Technol. Anal. Strateg. Manag.* **2021**, *33*, 900–913. [CrossRef]
35. Tayyab, M.; Sarkar, B. An interactive fuzzy programming approach for a sustainable supplier selection under textile supply chain management. *Comput. Ind. Eng.* **2021**, *155*, 107164. [CrossRef]
36. Doan, L.T.T.; Amer, Y.; Lee, S.-H.; Phuc, P.N.K.; Dat, L.Q. A comprehensive reverse supply chain model using an interactive fuzzy approach–A case study on the Vietnamese electronics industry. *Appl. Math. Model.* **2019**, *76*, 87–108. [CrossRef]
37. Rabbani, M.; Hosseini-Mokhallesun, S.A.A.; Ordibazar, A.H.; Farrokhi-Asl, H. A hybrid robust possibilistic approach for a sustainable supply chain location-allocation network design. *Int. J. Syst. Sci. Oper. Logist.* **2020**, *7*, 60–75. [CrossRef]
38. Gilani, H.; Sahebi, H.; Oliveira, F. Sustainable sugarcane-to-bioethanol supply chain network design: A robust possibilistic programming model. *Appl. Energy* **2020**, *278*, 115653. [CrossRef]

39. Zhang, W.; Reimann, M. A simple augmented-constraint method for multi-objective mathematical integer programming problems. *Eur. J. Oper. Res.* **2014**, *234*, 15–24. [CrossRef]
40. Pishvaee, M.S.; Razmi, J.; Torabi, S.A. Robust possibilistic programming for socially responsible supply chain network design: A new approach. *Fuzzy Sets Syst.* **2012**, *206*, 1–20. [CrossRef]
41. Awudu, I.; Zhang, J. Uncertainties and sustainability concepts in biofuel supply chain management: A review. *Renew. Sustain. Energy Rev.* **2012**, *16*, 1359–1368. [CrossRef]
42. Luhandjula, M.; Joubert, J.W. On some optimisation models in a fuzzy-stochastic environment. *Eur. J. Oper. Res.* **2010**, *207*, 1433–1441. [CrossRef]
43. Sahebjamnia, N.; Torabi, S.; Mansouri, S. Integrated business continuity and disaster recovery planning: Towards organizational resilience. *Eur. J. Oper. Res.* **2015**, *242*, 261–273. [CrossRef]
44. Mohammadkhani, A.; Mousavi, S.M. Assessment of third-party logistics providers by introducing a new stochastic two-phase compromise solution model with last aggregation. *Comput. Ind. Eng.* **2022**, *170*, 108324. [CrossRef]
45. Mohagheghi, V.; Mousavi, S.M.; Shahabi-Shahmiri, R. Sustainable project portfolio selection and optimization with considerations of outsourcing decisions, financing options and staff assignment under interval type-2 fuzzy uncertainty. *Neural Comput. Appl.* **2022**, *34*, 14577–14598. [CrossRef]