A two-phase sequential approach to design bioenergy supply chains under uncertainty and social concerns

Sobhan Razm, Alexandre Dolgui, Ramzi Hammami, Nadjib Brahimi, Stefan Nickel, Hadi Sahebi

A Two-Phase Sequential Approach to Design of Bioenergy Supply Chains under Uncertainty and Social Concerns

Sobhan Razm
PhD candidate of IMT Atlantique, France
sobhanrazm@gmail.com
IMT Atlantique, LS2N-CNRS, La Chantrerie, 4, rue Alfred Kastler, 44307 Nantes, France

Alexandre Dolgui
Full Professor, France
Head of the Department of Automation, Production and Computer Sciences (DAPI), IMT Atlantique
IMT Atlantique, LS2N-CNRS, La Chantrerie, 4, rue Alfred Kastler, 44307 Nantes, France

alexandre.dolgui@imt-atlantique.fr (corresponding author)

Ramzi Hamammi
Full Professor, France
Department of Supply Chain Management and Information Systems, Rennes School of Business
Director of the Area of Excellence on Green, Digital and Demand-Driven Supply Chain Management
Rennes School of Business, 2 Rue Robert d'Arbrissel, 35065 Rennes, France

ramzi.hammami@rennes-sb.com

Nadjib Brahimi
Associate Professor, department of supply chain management, Rennes School of Business, France
Director of MSc Data and Business Analytics
Rennes School of Business, 2 Rue Robert d'Arbrissel, 35065 Rennes, France

nadjib.brahimi@rennes-sb.com

Stefan Nickel
Full Professor, Germany
Chair in Discrete Optimization and Logistics, Karlsruhe Institute of Technology (KIT),
Director at Forschungszentrum Informatik (FZI), KIT,
Director at Karlsruhe Service Institute (KSRI), KIT.
stefan.nickel@kit.edu

Hadi Sahebi
Assistant Professor of Industrial Engineering at Iran University of Science and Technology, Iran
hadi_sahebi@iust.ac.ir

Abstract:

The use of renewable energies has become very attractive, because it protects the environment and boosts regional development. In this paper, a sustainable two-phase sequential approach is proposed for the design of bioenergy SCs under uncertainties. The first phase, integrating geographical information, social aspects, and multi-criteria decision-making techniques, helps find appropriate locations for the bio-refineries. High rates of unemployment, and high vulnerability to the variation in the markets in an economic crisis are considered as social concerns. Integrating these factors filters the areas for the second phase. The first phase reduces complexity in the computation of the problem, and helps set up sustainable development in the supply chain. In the second phase, to cope with the uncertainties in the bioenergy supply network, a robust model is introduced. It reduces the sensitivity to inaccurate input data, and the obtained solutions stay optimal when the parameters change slightly. In order to validate this two-phase sequential approach, a case study is investigated. The results of tests show that integrating the concepts of uncertainties and sustainability with geographical information of the area in a two-phase sequential approach outperforms the traditional models, and leads to the creation of 262 jobs. The jobs have a high impact on the surrounding area.

Keywords: Sustainable development; Bioenergy supply chains; Biomass; Uncertainty; Geographical information; Social sustainability.

1. Introduction

The increase in greenhouse gas (GHG) emissions has led to an abnormal increase of the earth's temperature, to climate changes, and, subsequently, to an increase in natural disasters. The photographs sent by emission measurement satellites have shown increasing greenhouse gas emissions and have provoked considerable concern. It caused the representatives of more than 100 countries participating in the 2015 United Nations Climate Change Conference in Paris to sign the Paris Agreement with the aim of reducing these emissions. The concerns were related to energy demand, and the environmental, economic, and social problems generated by using fossil fuels. These issues have led researchers to develop sources of renewable energy, which can augment regional development and protect the environment while still meeting the energy demand. Sources of renewable energy, bioenergy (heat and electricity) and biofuel (bioethanol, bio-oil, biodiesel, pellets) can be obtained from biomass in various ways. These renewable sources of energy can be used as substitutes for fossil fuels. Bioenergy and biofuel can decrease greenhouse gas (GHG) emissions [1] and create new jobs and more vitality in the areas concerned [2, 3]. One source of biomass is the feedstocks made from agricultural and forest residues. Forest residues contain: a) sawmill wastes: shavings, sawdust, hog fuel, chips; b) branches, leaves, tree tops, non-merchantable stems emanating from forest operations [4]. The agricultural residues contain wheat straw, sugarcane bagasse, corn stover, etc., which are not used as food, and originate from the wastes made from agriculture [5, 6]. Bioenergy, biofuel, and other bio-based products (chemicals, plastics, etc.) are the direct result of converting these residues through biochemical, chemical, and thermochemical basic processes [7-9]. The methods used to convert the forest/agricultural biomass into bioenergy/biofuel are thermochemical (combustion, pyrolysis, and gasification) and biochemical (producing ethanol through hydrolysis and fermentation) [8, 10].

In recent years, the importance of the design, implementation, and management of bioenergy SC has increased. One of the significant obstacles to development of a bioenergy supply chain is the cost of the bioenergy supply network. For instance, high costs could be incurred by supplying biomass to the biorefinery due to the economic and environmental implications of gathering and transporting biomass feedstock from the biomass supply site. The location of the biorefinery is fundamental in terms of reducing costs and GHG emissions (e.g. due to transportation). The location of the biorefinery is also important, because it can generate new jobs and sustainable development in the surrounding area [11].

When a wide geographic area is considered for planning, identifying the candidate locations of bio-refineries is a complex process requiring accurate assessments on the ground, so geographic information of the area is important. These locations should suit the possible environmental, economic and social interactions of the area. They should also have access to the biomass, resources and power required for the conversion technologies throughout the year [14, 15]. There is also a need to consider the uncertainties related to biomass availability, demand, transportation, operation, and costs in the design of the bioenergy SC. Uncertainties could make the design of the SC unfeasible, or render its performance suboptimal [12, 13]. Accordingly, it is important to integrate the concepts of sustainability and uncertainties as well as geographical information about the area into the planning and design of the bioenergy SC. Thus, the specific questions this study is seeking to answer are as follows:

- Which location strategy could be applied in order to design a bioenergy supply chain network in a large geographic area?
- What procedure could be adopted in order to achieve sustainable development in the supply network?
- Which approach could be followed in order to improve the stability of the bioenergy supply network under uncertain conditions?

In this paper, a sustainable two-phase sequential approach is proposed in order to design bioenergy SCs under uncertainties. The first phase tries to find the appropriate locations for the bio-refineries by integrating the geographic information system, the social aspects, and the multi-criteria decision-making techniques. In this phase, high rates of unemployment, and the high vulnerability of the areas to variations in the markets in an economic crisis, are considered as social concerns. Integrating these factors (the geographic information system, and the social sustainability) by using the multi-criteria decision-making techniques filters the areas to obtain appropriate locations as input for the second phase. The first phase augments the practicality of the supply network design, reduces complexity in the computation of the problem, and helps set up sustainable development. In the second phase, in order to cope with the uncertainties in the bioenergy supply network, a robust model is introduced to reduce the sensitivity to inaccurate input data. It means that the obtained optimal solutions are still optimal when the parameters change slightly.

In the remainder of this paper, a review of bioenergy supply chain network design is given in Section 2. The integrated two-phase approach is explained in Section 3. Section 4 formulates the deterministic and robust models of this approach. A case study is described in Section 5. Evaluation of the performance of the proposed method is presented in Section 6. Section 7 concludes and makes suggestions for future research.

2. Literature review

Modeling and optimization of bioenergy supply chains (SCs) have been attracting a great deal of attention from researchers recently. In bioenergy SC literature, from one point of view, many models only considered the economic aspect of the SC when designing the network. For instance, in the studies based on a bioenergy SC with agricultural and forest (AF) biomass, some researchers focused on geographical dispersion to find the sources and supply capacities [16-18]. Others worked on decisions related to the locations of bio-refinery and production capacity [19], and another group concentrated on the design of the supply chain (network) that generates biofuel from various types of AF biomass [4, 20, 21].

Bairamzadeh et al. [22] investigated the strategic and tactical decision levels of the biofuel supply chain based on AF biomass. The authors considered agricultural residues such as corn stover, wheat straw, barley straw and rice straw as feedstock biomass and proposed an MILP model to minimize the total cost of the SC by selecting the capacity, location, and technology of the biorefineries, as well as the amounts of production, inventory, allocation, and transportation. A hybrid robust optimization approach was suggested to cope with the uncertainties. Santibañez-Aguilar et al. [23] proposed an approach for optimal planning of the biomass residues obtained from crops such as sugar cane, corn, agave, palay rice in a processing system. The authors suggested a mathematical programming model involving mass balances to achieve the interconnections among different nodes of the supply chain. They considered constraints for the technologies in terms of capital investment and cost of production. The objective was to maximize the annual profit obtained from the revenue of selling products, minus the transportation cost, manufacturing cost, and raw material cost. They did not consider the related uncertainties in the model that may lead to a design for the SC network which is not feasible. Mohseni et al. [24] developed a mixed-integer linear programming model (MILP) model to minimize the total cost of the biodiesel supply chain. The study focused on third-generation biofuel, so the proposed mathematical model and approach are specific to a microalgae biomass supply chain. These studies only considered economic aspects of the supply chain, and social concerns or the concepts of sustainability related to the microalgae-based biodiesel SC were not investigated.

In terms of sustainable development, in [25] the authors proposed an MILP model to design a sustainable bioenergy supply chain network for switchgrass-based biomass. The model included economic, environmental and social objectives and aimed to find the maximum capacity in the biomass centers, the location and capacity of the power plants, and the amount of the collected and stored switchgrass. The authors used a hybrid method involving augmented ε-constraint and TOPSIS approach to consider preferences of decision-makers. The study did not consider any uncertainty. According to [26], designing a new biofuel supply chain can create jobs for local people in the area and protect the environment [2]. However, in the bioenergy supply chain literature, most of the studies just considered economic aspects of the supply chain, and less attention was given to the sustainability of the bioenergy SC, especially social aspects. Nevertheless, it is crucial to consider sustainability when designing bioenergy supply chains. Thus, there is a gap in the literature and a need to take into account, at the design stage, sustainability aspects, alongside economic effects [27]. Considering social criteria, in the article [26], the authors designed a bioethanol supply chain network using corn stover and wheat straw (lignocellusic biomass). They considered job opportunities as a social objective in a multi-objective MILP model to determine the location and capacity level of the facilities used in the biorefineries, inventory levels, and material flows. There are other studies in the literature which considered social aspects [28, 29]. Bijarchiyan and Sahebi [29] used the Guidelines for the Social Life Cycle Assessment of a Product (GSLCAP) method to find the social impact of a bioenergy supply chain network, and Carter and Rogers [28] introduced job creation as a social objective.

In terms of uncertainty, stochastic programming (two-stage) has been used in a large number of models. For example, a stochastic MILP model to design a biofuel SC under uncertainties of product price and cost of the feedstocks was proposed in [30]. The authors considered the net present value and the conditional value at risk as two objective functions in their model. A stochastic programming model under price and demand uncertainties which were solved by simulation and a Benders decomposition algorithm was proposed in [12] for the planning of a biofuel SC. A bioethanol SC considering demand as uncertainty was modeled by a stochastic MILP and solved with two-stage method in [31]. The sample average approximation method was used in that study in order to provide a set of configurations for facing uncertainty. Chen and Fan [32] presented a stochastic programming (two stage) model for resource allocation and strategic planning of a biofuel SC under uncertainty related to demand and supply. The authors solved it by using a decomposition algorithm based on Lagrange relaxation. In order to maximize the profit and decrease the carbon emissions with price, demand and supply uncertainties in a bioethanol supply chain, a two-stage stochastic MILP was proposed in [33].

When a large geographic area is considered for a bioenergy SC network, identifying the locations where the bio-refineries may be installed is very important, because the network structure, costs, social performance, and environment are affected by these decisions. The methods used in the existing publications are not always clearly out. For instance, some researchers considered sets of locations which were as large as possible, covering most of the desired territory, to obtain more opportunities. Some others considered a continuous territory in their facility location models by assuming that the facilities could be placed anywhere [17]. These methods present some problems such as: 1) they cannot guarantee that optimal places are chosen in the whole of the desired territory, 2) those that considered continuous territory in their facility location models [17] usually restricted their models to a limited number of levels and parts, 3) also when the planning space increases, not only the computational complexity is significantly increased, but functionality is also severely limited [34]. What is why, the conventional agricultural and forest (AF) biomass SC models [19, 35, 36] usually focused on limited and predetermined candidate locations. In this case, simultaneously considering geographical information and social sustainability of the wide geographical territory is very important to select such candidate locations. Nevertheless, the existing models usually did not take them into account. By embracing the Geographic Information System (GIS) and the sustainability, and by using the multi-criteria decision-making techniques it is possible to consider more map layers in order to determine more appropriate places for bio-refineries. Moreover, if the bioenergy SC decisions do not take uncertainties sufficiently into account, the design model will not be trustworthy nor feasible. These are the factors which motivate this paper versus the state of the art.

Table 1 shows the outcomes of the literature review concerning the bioenergy SC problem. It shows that there is an essential research gap to optimize bioenergy supply chains by considering a two-phase sequential approach containing the geographical information, sustainability, multi-criteria decision-making techniques and uncertainty conditions. This study makes an effort to fill this gap.

Consequently, this paper includes the following contributions: 1) it develops a model for designing and planning the agricultural/forest residues-to-bioenergy supply chains; 2) it proposes a two-phase approach to solve the introduced SC model; 3) it integrates geographical information, social sustainability, and the multi-criteria decision-making techniques to find appropriate locations for bio-refineries; 4) it uses robust optimization to hedge against uncertainty; and 5) it validates the developed two-phase approach by applying it to a case study.

3. Problem definition

The bioenergy SC of AF residues is a complex multi-phase supply network that starts with the supply of raw materials (biomass) for bio-refineries and finishes with the market end-products. In such a network, the bio raw materials contain non-merchantable AF residues usually collected from piles left at the roadsides of the harvesting blocks and from plants that produce AF products. Next, these raw materials are sent to bio-refineries installed as independent units or set up near plants that produce AF products. Proximity reduces biomass transport/management costs [14]. In this paper, it is considered that bio-refineries can also act as suppliers of renewable energy for AF plants. Different biochemical, chemical, and thermochemical processes can change the biomass into biofuel, pellets, heat, electricity, etc. The biomass type and the features of the desired products determine type of technology [8]. The bioenergy produced (electricity/heat) is either used in the bio-refinery or sold to local heat grids/system. The biofuel products are sent to various markets.

Figure 1 shows the studied structure of the SC that obtains bioenergy from agricultural and forest residues. In this figure, S is the biomass supply site, R represents the various types of AF biomass, and B are the candidate locations for bio-refineries. Conversion technology A can be used at any candidate location and these technologies produce the following products: 1) bioenergy E for local use such as supplying power for the biofuel conversion technologies, forest product plants, electricity grids, etc.; and 2) different product types of biofuel F which are traded in market C. If it is economical, the heat and electricity needed for conversion technologies can be obtained from the currently used energy.

Table 1: This study vs. the bio-energy supply chain literature

Article	Approach (Modeling) Mathematical Programming			Geographical information	Objective function	Decisions (Strategic)	Facilities			Decisions (Tactical)				Social sustainability	MCDM techniques	Uncertain parameters				Uncertainty modelling approach	Final products			
	MoMILP	MILP	MINLP			Sourcing	Location	Capacity	Technology	Biomass allocation	Biofuel production	Transportation	Inventory planning			Biomass supply	Demand of products	Price of products	Costs		Electricity	Pellet	Heat	Biofuel (bioethanol, bio-oil, biodiesel)
(Dal-Mas et al., 2011)		X		X	3,4	X	X	X		X	X	X						X		Scenario-based stochastic programming				X
(Gonela et al., 2015)		X			2	X	X	X		X	X	X	X	X		X	X	X		Scenario-based stochastic programming				X
(Kostin et al., 2012)	X				3,4		X	X	X	X	X	X	X				X			Two-stage stochastic programming				X
(Saghaei et al., 2020)			X		1	X	X	X		X			X			X	X			Two-stage stochastic programming	X			
(Balaman and Selim, 2015)	X				2-7		X	X		X	X	X	X			X			X	Fuzzy multi-objective modeling approach	X			
(Awudu and Zhang, 2013)		X			2					X	X	X	X				X	X		Stochastic programming				X
(Santibañez-Aguilar et al., 2019)			X	X	2	X	X	X	X	X	X	X	X		X					-	X		X	X
(Mohseni et al., 2016)		X		X	1	X	X	X		X	X	X	X		X	X	X		X	Robust convex Programming (Bertsimas & sim's approach)				X
(Chen and Fan, 2012)		X		X	1		X	X		X	X	X				X	X			Two-stage stochastic programming				X
(Marvin et al., 2012)		X		X	3	X	X	X		X	X	X						X		Sensitivity analysis				X
(Razm et al., 2019b)		X			3	X	X	X	X	X	X	X					X			Two-stage stochastic programming	X	X	X	X
(Osmani and Zhang, 2013)		X			2	X	X	X		X	X	X				X	X	X		Two-stage stochastic programming				X
(Khishtandar, 2019)			X		1		X			X						X				Fuzzy chance-constrained programming	X			
Proposed model		X		X	1	X	X	X	X	X	X	X	X	X	X	X	X		X	Robust convex Programming (Bertsimas & sim's approach)	X	X	X	X

1= minimizing (expected) total cost/annual cost/unit cost. 2= maximizing (expected) total profit/annual profit/annual income/net cash. 3= maximizing (expected) net present value. 4=minimizing expected (conditional) value at risk/investment financial risk. 5-minimaizing investment cost. 6= minimizing annual transportation cost. 7= minimizing annual purchasing cost. 8= minimizing annual operational cost.

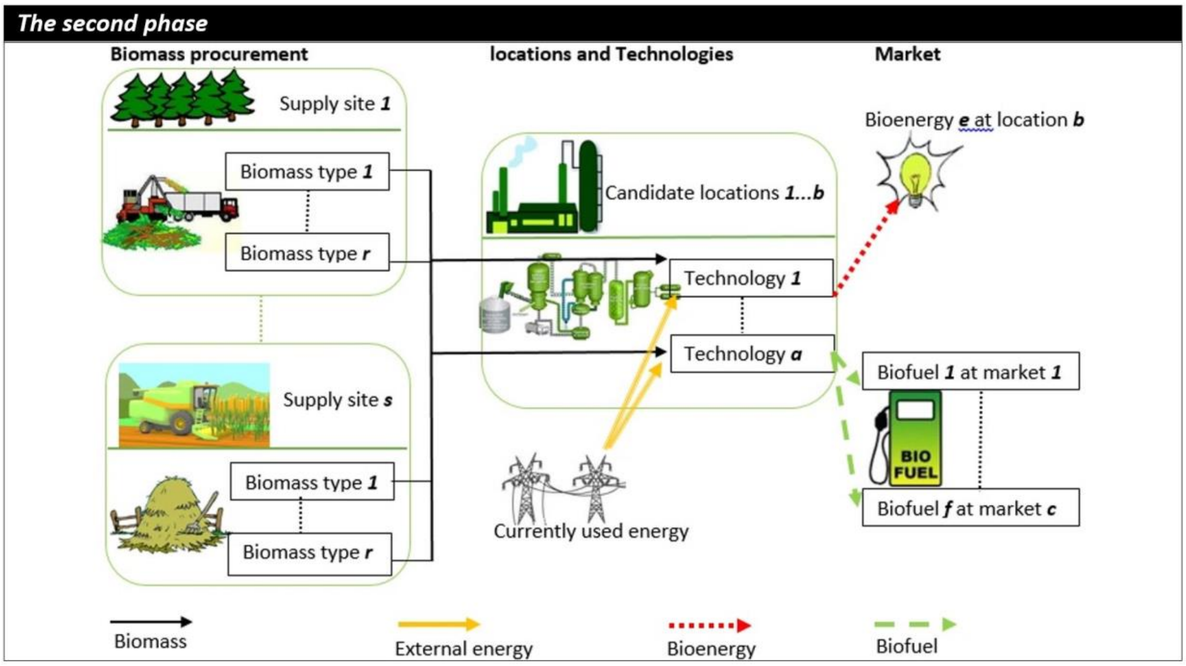

Figure 1: Configuration of the bioenergy supply chain network.

3.1. The proposed two-phase approach

The design process for the SC network that converts AF biomass to bioenergy involves two phases. In the first phase, as shown in Figure 2, the appropriate locations that could be candidates for bio-refineries are selected based on geographical information and social concerns by using multi-criteria decision-making techniques. These locations are then used as inputs in the model for the second phase to yield the final locations of the bio-refineries and the entire supply network minimizing costs.

3.1.1. The first phase of the proposed two-phase approach

Identifying the candidate locations to set up bio-refineries is a complex process requiring accurate assessments over a wide geographic area. These locations should conform to the regions' possible environmental, economic and social interactions, and should have access to biomass/resources, and the power required for conversion technologies all through the year [14, 15]. Accordingly, a set of criteria grouped into those related to resources, environment, society, and economy is determined to find the location of bio-refineries according to the information existing in literature [42-45] and also quantitative/ qualitative information which can be obtained from consulting the experts of the national mapping agency of each country.

In the first phase, with experts of the national mapping agency of each country as decision-makers, the AHP method as a well-known Multi-Criteria Decision Making (MCDM) technique [46] can be used to weight every map layer and the specific criteria to select candidate locations. The layers are then overlaid on the base map using GIS overlay analysis. Each layer's allocated importance weight is multiplied by the value of each digital cell considered on the base map. Then, all of them come together using a summation in order to generate the digital cells' total suitability scores on the base map [47]. Next, a suitability index is calculated that divides the area studied into a range between high suitability and low suitability. Finally, the first phase achieves its goal by proposing high-suitability, favorable locations in the considered geographical area.

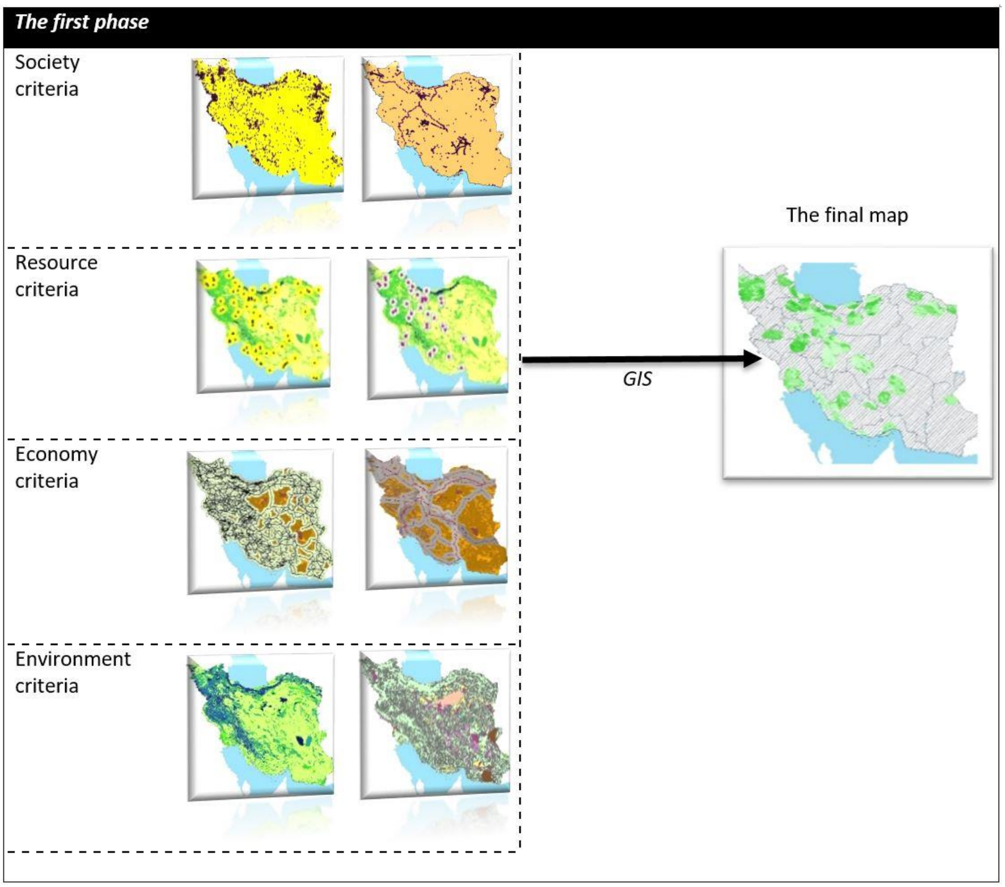

Figure 2: Different aspects of geographical information in the bioenergy supply chain.

3.1.1.1 The social dimension of the bioenergy supply network (BE-SN)

For example, given the research done by Isfahan University of Technology's college of agricultural engineering, Iran's Ministry of Economic Affairs and Finance prepared a vulnerability index Ξ for agriculture and forest, that withstands the variations in the markets of AF products. The economic variety in the territory is introduced by the $variety\ index\ \Pi$, which varies between 0 and 100. Value 0 means the territory relies totally on one section, whereas 100 means the territory relies identically on each section. A portion of the recruitment income that is earned from forest and agricultural sections in the territory is shown by the $dependency\ index\ \Delta$ which is in between 0 and 1. Thus, the index Ξ is introduced as the $index\ of\ forest\ and\ agriculture\ vulnerability$ of the different territories (e.g. different states of a country), scoring from 0 until 100 after normalizing:

$$\Xi = \Delta \times (100 - \Pi).$$

The value 100 means the territory is the most vulnerable. For instance, the values of Ξ for some regions are shown in Table 3 (www.amar.org.ir), they can be obtained from each country's statistics office.

Table 3:

The values of Ξ for for each territory.

territory	***b1***	***b2***	***b3***	***b4***	***b5***	***b6***	***b7***	***b8***	***b9***	***b10***
Ξ	18	62	14	23	19	17	15	53	50	43
territory	***b11***	***b12***	***b13***	***b14***	***b15***	***b16***	***b17***	***b18***	***b19***	***b20***
Ξ	16	42	44	48	30	41	12	23	49	13
territory	***b21***	***b22***	***b23***							
Ξ	55	22	20							

Concentrating on the territories with high level of unemployment and with high vulnerability can lead to social advantages. In other words, if jobs with higher levels of employment are offered in the territories with high level of vulnerability, more social advantages can be obtained [48].

Depending on the job losses in the other production facilities for residents of territories due to the economic crisis, various job categories are proposed in the SC of bio-refineries that are relevant to the skills of the individuals in these territories.

For instance, the farmers lost jobs can be replaced by work in the combustion stations, and the pyrolysis technology stations can provide jobs for individuals previously working in the corporations relating to oil. For example, according to the Iranian statistics office (www.amar.org.ir), a large number of farming jobs were destroyed in the last economic crisis, so their unemployment rate is high (equal to 11.23%). These farmers could be used in the combustion centers. If the social impact of the jobs created for local people is developed in this way, there will be social advantages.

After consulting the Renewable Energy and Energy Efficiency Organization (www.satba.gov.ir), the jobs created for local people by installing the bio-refinery are classed into three main categories depending on the average unemployment rate (Λ_w). There are jobs related to combustion, pelletizing, and the pyrolysis section (w), (see Table 4).

It should be mentioned that these unemployment rates can be obtained from the statistics office of each country, so Table 4 can be adapted to other case studies or countries.

Given the vulnerability and unemployment rate in the bio-refineries' territory, the social impact of the jobs created in the category w in the territory b could be obtained as follows:

$$\Psi_{w,b} = \Lambda_w \times \Xi_b \tag{S1}$$

Therefore, in order to maximize the social impact in the territories where bio-refineries will be established, the areas with high vulnerability indexes are considered using the statistics office of each country. These areas are used as input (digital map) for GIS. Then, by using the ring buffers as defined in the ArcGIS Software at different distances (e.g., 1.5, 4, 5, 17, 70, and 100 km from the central locations), the areas being analyzed are limited and those outside the ring buffers (spaces) are omitted. This method is also used for the areas with high rates of unemployment in order to obtain the second digital map layer of society criteria.

Table 4

The job class and its average unemployment.		
Class (w)	**Description**	**Average unemployment rate (Λ_w)**
1. Combustion	This class of jobs has a revenue between \$50,000 and \$55,000 per year. The revenue is able to change in the specific range considering the technologies' capacities and the requested variable and fixed work hours. For example, jobs related to burning of agriculture and forest biomass to generate heat and electricity, or periodic maintenance of combustion technology like the **biomass** boiler and steam turbine.	**11.23%**
2.Pelletizing	This class of jobs has a revenue between \$55,000 and \$60,000 per year. The revenue is able to change in the specific range considering the technologies' capacities and the requested variable and fixed work hours. For example, working with technologies which are specific to generate pellets, or preprocesses which are requested in each period before performing the main process of generating pellets.	**6.55%**
3.Pyrolysis	This class of jobs has a revenue more than \$60,000 per year. The revenue is able to change in the specific range considering the technologies' capacities and the requested variable and fixed work hours. For example, the hourly jobs for the generating process with pyrolysis technologies or the jobs with fixed hours for constant presence of the experts beside the facilities in each period.	**12.35%**

3.1.1.2. The resources of the bioenergy supply network (BE-SN)

The resources required include forest residues and agricultural remains. The former involves harvesting residues such as non-merchantable, small diameter, low quality logs, tree tops, and branches (not suitable for either pulp production or lumber) and sawmill waste. The latter includes agricultural waste and non-food crops like corn stover and wheat straw.

These raw materials (biomass) could usually be gathered from many aggregated cutting blocks and agricultural lands. One of the signs of biomass availability is the presence of procurement centers/ forest product mills. Obviously, the farther the location of a bio-refinery is from the procurement centers/forest product mills, the higher the biomass accessibility cost will be. Accordingly, the proposed method can use the ring buffers at different distances (e.g., of 3, 12, 25, 75, and 100 km) around the existing procurement centers/forest product mills to make the biomass accessibility less expensive. It is worth mentioning that these residues ordinarily have no use in any other industry, and are usually disposed by burning or in landfill [49, 50].

Supplying energy from resources is another issue for biomass conversion technologies in the bio-refineries. The required energy can be supplied either by the bioenergy generated in the bio-refineries or from the electricity of the power plants that are the current energy sources.

Transferring electricity and energy from remote areas is costly. If energy sources are far from bio-refineries, they will induce heavy energy costs for the SC [50]. Hence, using the ring buffers (spaces) at different distances (e.g. 1.5, 4, 5, 17, 70, and 100 km) from the energy sources limits the areas being analyzed, and those outside the ring buffers (spaces) are omitted.

3.1.1.3. The economic criteria in the locations of bio-refineries

The total transportation cost in the bioenergy/biofuel SC is quite high. Connecting bio-refineries to the country roadways/railways networks is a significant problem that imposes a high cost on the SC which can make it economically unprofitable. To solve this problem, different spaces are used around the country's main roadways and railways to exclude areas outside these spaces [51].

3.1.1.4. The environmental criteria of BE-SN

- Land use: Considering environmental issues and other features of bio-refineries, lands that have less usage problems should be selected [15, 42]. For example, agriculture is an important element in the economy of many countries. Conversion of agricultural lands can be not allowed according to the laws of the country. Therefore, bio-refineries cannot be built on these lands. Hence, other remaining regions (barren lands, woodlands, pastures, shrubs, herbaceous) will have priority. Note that these laws may differ from country to country, so by considering new conditions the remaining regions and their weights on the map layers may be changed.
- Land slope: Sloping surfaces are not suitable for building bio-refineries because they increase construction problems due to the costs of such activities as cutting, filling, earthwork and erosion prevention [52]. To reduce these costs, the study of suitable locations could be limited to land with less slopes (e.g. less than 5 degrees), the digital elevation model and the ''surface'' command in the ArcGIS Software can be used in this part.

3.1.2. The second phase of the proposed two-phase approach

The second phase is aimed at designing an optimal SC network (SCN) that produces bioenergy from biomass to ensure that all the SC decisions, from supplying biomass to the end products (biofuel and bioenergy) received by customers, are made and integrated optimally. The decisions made at this phase are:

- Determining the raw material flow between the suppliers and bio-refineries and that of the bioenergy and biofuels between bio-refineries and customers.
- Selecting biomass suppliers.
- Determining the optimal locations of bio-refineries from the appropriate locations identified in the first phase.
- Determining the type/capacity of the biomass conversion technologies used in each bio-refinery.
- Proposing the biofuel production rate and inventory planning for production during the year.

These decisions are affected by uncertainties such as variable access to biomass due to seasonal variations, and uncertain cost factors due to large-scale bioenergy/biofuel production [30, 31].

Stochastic programming or robust optimization (RO) can be used in order to cope with these kinds of uncertainties in the optimization problems [53]. Although stochastic programming (SP) is a powerful tool for dealing with uncertainties, it suffers from some obvious flaws such as: 1) it needs the probability distribution information for values of the parameters under uncertainty, but in real life, it is not usually possible to determine this distribution accurately because of the shortage of historical data; 2) it generally leads to complexity in the computations for models in real world problems because it needs many scenarios to model uncertainties [54]. Conversely, RO, which is capable of preserving the primary model's computational tractability [55], is a free distribution method aimed at finding the solution (worst case) according to a predetermined set of uncertainties. It could be used to prevent input data uncertainty in the problem, and stays robust against any perturbations. Furthermore, besides the lack of information to find the probability distributions for uncertain parameters considered in this study, there also are different fluctuating factors that can affect these uncertain parameters such as seasonality of biomass or different cost factors due to the large scale of the network. The nature of uncertainty for these parameters is characterized by deep uncertainty. This means for each uncertain parameter, a known interval is expressed. The interval is expressed without assuming a specific distribution of probabilities [22].

The interval uncertainty in robust optimization was first presented in [56]. The author considered all the uncertain parameter values in the worst case to provide maximum protection against uncertainties. Nevertheless, this is not realistic, because at the same time the whole set of uncertain parameters may result in the worst value, so the idea was excessively over-conservative. This theory was then developed in [57, 58] and, under an ellipsoid uncertainty set, a robust counterpart formulation to control the solution's conservatism level was presented. The authors developed a robust optimization methodology in which the linear program (LP) is changed to a convex nonlinear program (NLP), which is more complicated as regards the computations. Next, in [59] an approach was developed that can control the conservatism level and preserve the linearity of the model as well. It will be used in this study, i.e. for the design of the bio-energy SC, the two-phase approach proposed in this paper is based on a robust model adopting the Bertsimas-Sim ideas [59].

3.2. Analytical Hierarchy Process (AHP)

The Analytical Hierarchy Process is a decision-making technique for extracting the weights of criteria in the problems involving competitive and multiple objectives (a complex decision-making problem). It generally involves three phases [60]: 1) the problem is broken down into a descending hierarchical structure where the objective stands at the upper level, the criteria lie below it, and then sub-criteria are categorized; 2) the paired comparison matrix is computed for this hierarchy at each level, in such a way that, based on the 9-point scale, each element lies in a 1 to 9 interval (from the importance of the row criterion in relation to its column criterion), 1 means equal preference and 9 means strongly preferred; and, finally, 3) the principal eigenvalue and also the corresponding normalized eigenvector of the matrix are calculated to derive the relative importance weights of the criteria being compared [68].

It is necessary to justify the consistency of the judgments in order to ensure the results of the weighting process. For a paired comparison matrix, the consistency index is obtained using the following equation:

$$CI = {}^{(\lambda_{max} - n)}\big/_{(n-1)}$$

$$CR = {}^{CI}\big/_{RI}$$

where *CI* is the consistency index, λ_{max} is the largest matrix eigenvalue, and *n* is the matrix order.

CR (the acronym of consistency rate) compares *CI* with *RI* (the acronym of random index). *CR* is used for a better understanding of the *CI* value. *CR* < 0.1 means consistency of the formed matrix and reliability of the calculated weights. Otherwise, reformation, from the beginning, of the pair-wise comparison matrix would be necessary.

3.3. Robust optimization approach

To briefly describe the Bertsimas-Sim's approach [59], let us examine the following LP:

$$
\begin{aligned}
& Min\ cx \\
& st: \sum_j \tilde{a}_{ij} x_j \ \geq b_i \qquad \forall\, i \qquad \text{(R1)} \\
& x \in X
\end{aligned}
$$

where $\tilde{a}_{ij}$ can be uncertain and J_i is the set of uncertain parameters of row *i*. The $\tilde{a}_{ij}$ is a random variable on a support $\left[a_{ij} - \widehat{a_{ij}}\, , a_{ij} + \widehat{a_{ij}}\ \right]$ where a_{ij} is the nominal value and $\widehat{a_{ij}}$ is the perturbation amplitude. The parameter Γ_i (uncertainty budget), that may not be integer, can be used in each constraint *i* in order to make a trade-off for the solution's conservatism level and the model's robustness. It takes values between [0, $|J_i|$] where$|J_i|$ shows the cardinality of set J_i, and aims at forcing $\lfloor \Gamma_i \rfloor$ parameters to acquire their values at worst case, then goes for next one ($\tilde{a}_{it}$) and moves the next one to its worst value from its nominal value by $(\Gamma_i - \lfloor \Gamma_i \rfloor)\widehat{a_{it}}$. Hence, the following form, which is nonlinear, can be considered as the model's robust counterpart mentioned in (R1):

$$
\begin{aligned}
& Min\ cx \\
& st: \sum_j a_{ij} x_j - \max_{\{S_i \cup \{t_i\} | S_i \subseteq J_i, |S_i| = \lfloor \Gamma_i \rfloor,\ t_i \in J_i \setminus S_i\}} \left\{ \sum_{j \in S_i} \hat{a}_{ij}\, x_j + (\Gamma_i - \lfloor \Gamma_i \rfloor) \widehat{a_{it_i}}\, x_j \right\} \geq b_i \qquad \forall\, i \quad \text{(R2)} \\
& X \geq 0
\end{aligned}
$$

where S_i shows coefficients which take the worst value and t_i demonstrates the one that varies if Γ_i is not an integer.

The constraint *i*'s protection function, $(max_{\{S_i \cup \{t_i\} | S_i \subseteq J_i, |S_i| = \lfloor \Gamma_i \rfloor, t_i \in J_i \setminus S_i\}} \{\sum_{j \in S_i} \hat{a}_{ij} \left|x_j^*\right| + (\Gamma_i - \lfloor \Gamma_i \rfloor) \widehat{a_{it_i}} \left|x_j^*\right| \})$, considering x_j^* as optimal solution could be rewritten in the linear form as follows:

$$
\begin{aligned}
& Max \sum_{i \in J_i} \widehat{a_{ij}} \left|x_j^*\right| v_{ij} \\
& st: \sum_{i \in J_i} v_{ij} \leq \Gamma_i \qquad \forall\, i \qquad \text{(R3)} \\
& 0 \leq v_{ij} \leq 1 \qquad \forall\, i, j \in J_i
\end{aligned}
$$

Due to the feasibility of the problem (R3), and also because it is bounded for all Γ_i, its dual pair is also bounded and feasible with the identical objective value according to the strong duality property. If ϱ_i and Υ_{ij} (dual variables) are defined, the dual problem for (R3) can be shown as follows:

$$
\begin{array}{lll}
Min\ \Gamma_i \varrho_i + \sum_{j \in J_i} \Upsilon_{ij} & & \\
st\text{: } \varrho_i + \Upsilon_{ij} \geq \hat{a}_{ij}|x_j^*| & \forall\, i, j \in J_i & \text{(R4)} \\
\Upsilon_{ij} \geq 0 & \forall\, i, j \in J_i & \\
\varrho_i \geq 0 & \forall\, i &
\end{array}
$$

Substituting (R4) in (R2), the linear robust counterpart will be as follows:

$$
\begin{array}{lll}
Min\ \ cx & & \\
st\text{: } \sum_{i} a_{ij}\ x_j - \Gamma_i \varrho_i - \sum_{j \in J_i} \Upsilon_{ij} \geq\ b_i & \forall\, i & \text{(R5)} \\
\Upsilon_{ij}, \varrho_i, x_j \geq 0 & \forall\, i, j \in J_i &
\end{array}
$$

To apply the robust equation to constraints where uncertainties only affect the right-hand side (RHS), consider that of (R1). Here, also, there is the interval $[b_i - \widehat{b_i}, b_i + \widehat{b_i}]$ meaning that the distribution of each uncertain parameter is symmetric and bounded, but Γ_i' (uncertainty budget) takes values between 0 and 1. Considering these definitions, problem (R1)'s robust counterpart can be written as follows:

$$
\begin{array}{lll}
Min\ \ cx & & \\
st\text{: } \sum_{i} \tilde{a}_{ij}\ x_j\ \geq\ b_i + max\ \widehat{b_i} v_i & \forall\, i & \text{(R6)} \\
0 \leq v_i \leq \Gamma_i' & \forall\, i & \\
x \geq 0 & &
\end{array}
$$

The equivalent of equation (R6) is the following linear optimization problem:

$$
\begin{array}{lll}
Min\ \ cx & & \\
st\text{: } \sum_{j} \tilde{a}_{ij} x_j\ \geq b_i + \Gamma_i' \widehat{b_i} & \forall\, i & \text{(R7)} \\
x \geq 0 & &
\end{array}
$$

It is worth noting that when Γ_i' = 0, there is no protection against uncertainty, and when Γ_i' = 1, there is full protection against uncertainty. When Γ_i' varies between 0 and 1, it can control the solution's conservatism level. Bertsimas and Sim [59] suggest that if decision makers change the value of Γ_i by considering an upper bound for the constraint violation's probability $[exp(-\Gamma_i^2/2|J_i|)]$, they can adjust constraint *i*'s conservatism/reliability level.

4. Model formulation

This section has two objectives. Firstly, it shows the development of a deterministic mixed integer linear programming model (MILP) to optimize the strategic design of the bioenergy SC. Secondly, it presents the MILP robust model considering uncertain parameters. Before formulating the problem, a verbal description is presented to understand the model better.

$$\begin{aligned}
&\boldsymbol{Minimization\ of\ total\ costs} = \ Procurement\ biomass\ costs \\
&+Biomass\ transportation\ cost + Biofuel\ transportation\ costs + \ Fixed\ opening\ costs \\
&+Variable\ production\ costs + Energy\ purchase\ costs + \text{Inventory holding costs} \\
&\boldsymbol{Subject\ to}: \\
&Resource\ availability\ constraints, Biomass\ flow\ constraints, \\
&Bioenergy\ and\ biofuel\ balance\ equations, Bioenergy\ and\ biofuel\ flow\ constraints, \\
&Production\ capacity\ \ equations, Inventory\ balance\ equations, \\
&Satisfaction\ of\ the\ demand, Binary\ limitations\ on\ the\ relative\ decision\ variables
\end{aligned}$$

4.1. Deterministic Bioenergy Supply Network (DBE-SN) model

Using Table 2, the following DBE-SN model is formulated.

4.1.1. Objective function

The objective function (1) minimizes the total costs of the SC throughout the planning horizon, including costs of supplying biomass (purchasing/collecting), transportation of biomass to bio-refineries, transportation of biofuel from bio-refineries to markets, fixed costs (annual investments), variable production costs, and energy costs for launching technologies, i.e. that part of the energy required by the bio-refinery supplied by the available energy sources. Also, the inventory holding costs of different biofuel types are also considered in the objective function. It is worth noting that the biomass is not stocked in this case to prevent its deterioration and dehydration from one year to another. Bioenergy storage is also dismissed because it is either impossible or not economical.

$$Min\ Total\ Cost = \sum_{r\in R}\sum_{s\in S}\sum_{b\in B}\sum_{t\in T} \widetilde{\varsigma^{B}_{r,s,t}} \cdot U_{r,s,b,t}$$

$$+\sum_{r\in R}\sum_{s\in S}\sum_{b\in B}\sum_{t\in T} \widetilde{\varsigma^{B,T}_{r,s,b,t}} \cdot U_{r,s,b,t}$$

$$+\sum_{f\in F}\sum_{b\in B}\sum_{c\in C}\sum_{t\in T} \widetilde{\varsigma^{B,T}_{f,b,c,t}} \cdot P^{M}_{f,b,c,t}$$

$$+\sum_{a\in A}\sum_{b\in B}\sum_{t\in T} \widetilde{\varsigma^{F}_{a,b,t}} \cdot Y_{b,a,t}$$

$$+\sum_{r\in R}\sum_{b\in B}\sum_{a\in A}\sum_{t\in T}\widetilde{\varsigma^{V}_{b,a,t}} \cdot U^{U}_{r,b,a,t}$$

$$+\sum_{e\in E}\sum_{b\in B}\sum_{t\in T}\widetilde{\varsigma^{E}_{e,b,t}} \cdot J^{C}_{e,b,t}$$

$$+\sum_{f\in F}\sum_{b\in B}\sum_{t\in T}\widetilde{\varsigma^{H}_{f,b}} \cdot I^{B}_{f,b,t} \qquad (1)$$

4.1.2. Constraints

Constraints (2) ensure that amount of the biomass *r* coming from supplier *s* could not be more than the available biomass.

$$\sum_{b\in B} U_{r,s,b,t} \le \widetilde{\beta_{r,s,t}} \qquad \forall r \in R, s \in S, t \in T \qquad (2)$$

Constraints (3) ensure that the total biomass shipped from various resources is equal to that used by all conversion technologies at any location and in any period.

$$\sum_{s\in S} U_{r,s,b,t} = \sum_{a\in A} U^{U}_{r,b,a,t} \qquad \forall r \in R, b \in B, t \in T \qquad (3)$$

Constraints (4) ensure the type of biomass required for each technology.

$$U^{U}_{r,b,a,t} \le \varphi \cdot \psi_{r,a} \qquad \forall r \in R, b \in B, t \in T \qquad (4)$$

Constraints (5) and (6) guarantee that the total bioenergy and biofuel produced by each technology is equal to its conversion efficiency. Types of technologies and biomass are considered in this conversion efficiency because, depending on the quality and amount of energy involved, various biomass types have different efficiencies and can be converted through different conversion methods.

$$P_{f,b,a,t} = \sum_{r\in R} \gamma_{f,r,a} \cdot U^{U}_{r,b,a,t} \qquad \forall f \in F, b \in B, a \in A, t \in T \qquad (5)$$

$$G_{e,b,a,t} = \sum_{r\in R} \gamma_{e,r,a} \cdot U^{U}_{r,b,a,t} \qquad \forall e \in E, b \in B, a \in A, t \in T \qquad (6)$$

Constraints (7) and (8) ensure the maximum throughout for final products producing by different technologies in each period, and show that production will continue in bio-refinery *b* if technology *a* is installed and works there ($Y_{b,a,t} = 1$).

$$P_{f,b,a,t} \leq \xi^{M}_{a,f} \cdot Y_{b,a,t} \qquad \forall f \in F, b \in B, a \in A, t \in T \quad (7)$$

$$G_{e,b,a,t} \leq \xi^{M}_{a,e} \cdot Y_{b,a,t} \qquad \forall e \in E, b \in B, a \in A, t \in T \quad (8)$$

Constraints (9) and (10) permit that, in each period, biofuel and bioenergy should exceed a minimum utilization capacity and prevent the installation of idle technologies.

$$P_{f,b,a,t} \geq \xi^{M}_{a,f} \cdot Y_{b,a,t} \cdot \widetilde{\mu^{m}_{f}} \qquad \forall f \in F, b \in B, a \in A, t \in T \quad (9)$$

$$G_{e,b,a,t} \geq \xi^{M}_{a,e} \cdot Y_{b,a,t} \cdot \widetilde{\mu^{m}_{e}} \qquad \forall e \in E, b \in B, a \in A, t \in T \quad (10)$$

Constraints (11) make sure that the biofuel's amount for the markets should be equal to the amount produced at location *b* in any period.

$$\sum_{c \in C} P^{M}_{f,b,c,t} = \sum_{a \in A} P_{f,b,a,t} \qquad \forall b \in B, f \in F, t \in T \quad (11)$$

Constraints (12) ensure that the bioenergy used by the technology installed in each bio-refinery, plus the amount sold to customers (outside of the bio-refinery), should equal the total amount produced in the bio-refinery in each period.

$$G^{S}_{e,b,t} + G^{U}_{e,b,t} = \sum_{a \in A} G_{e,b,a,t} \qquad \forall e \in E, b \in B, t \in T \quad (12)$$

Constraints (13) and (14) show the demand limitations for bioenergy and biofuel products.

$$\widetilde{\delta^{m}_{f,c,t}} \cdot M_{f,c} \leq \sum_{b \in B} P^{M}_{f,b,c,t} \leq \widetilde{\delta^{M}_{f,c,t}} \cdot M_{f,c} \qquad \forall f \in F, c \in C, t \in T \quad (13)$$

$$\widetilde{\delta^{E,m}_{e,b,t}} \leq G^{S}_{e,b,t} \leq \widetilde{\delta^{E,M}_{e,b,t}} \qquad \forall e \in E, b \in B, t \in T \quad (14)$$

Constraints (15) guarantee that the energy required for conversion technologies in each bio-refinery is equal to the energy that can be met by the bioenergy produced in the bio-refinery plus that supplied from other currently used sources of energy at that location.

$$\sum_{r \in R} \sum_{a \in A} \vartheta^{I,C}_{e,r,a} \cdot U^{U}_{r,b,a,t} = G^{U}_{e,b,t} + J^{C}_{e,b,t} \qquad \forall e \in E, b \in B, t \in T \quad (15)$$

Constraints (16) ensure that all the biofuel distributed to the markets throughout each period (i.e. $\sum_{c\in C} P^{M}_{f,b,c,t}$) , plus the biofuel inventory at the end of period *t* (i.e. $I^{B}_{f,b,t}$) should not exceed the biofuel produced by technology *a* in period *t* (i.e. $\sum_{a\in A} P_{f,b,a,t}$) plus the inventory at the end of period *t*-1 (i.e. $I^{B}_{f,b,(t-1)}$).

$$\sum_{a\in A} P_{f,b,a,t} + I^{B}_{f,b,(t-1)} \geq \sum_{c\in C} P^{M}_{f,b,c,t} + I^{B}_{f,b,t} \qquad \forall f \in F, b \in B, t \in T \qquad (16)$$

Constraints (17) indicate that the total biofuel produced in all bio-refineries in each period should be at least equal to the total targeted demand in each period (throughout the considered country or geographical area).

$$\sum_{b\in B}\sum_{c\in C} P^{M}_{f,b,c,t} \geq \widetilde{\varpi^{T}_{f,t}} \qquad \forall f \in F, t \in T \qquad (17)$$

Constraints (18) ensure persistence in the conversion processes after the bio-refineries are installed.

$$Y_{b,a,t} \geq Y_{b,a,(t-1)} \qquad \forall a \in A, b \in B, t \in T \qquad (18)$$

Constraints (19) and (20) are to prevent the model from selecting more than one technology for generating any kind of biofuel and bioenergy. Index a^{e} presents a subset of the technologies which can produce the bioenergy of type *e*, index a^{f} presents one that can produce type *f* bioenergy. It is worth noting that, when the installed technologies' numbers are limited to the available biomass or to the demand for products, constraints (19) and (20) could be eliminated. Therefore, when the objective function does not consider such limiting factors as high costs, the total number of technologies installed in each bio-refinery may not be limited for samples with large available biomass and high product demand.

$$\sum_{a^{e}\in A} Y_{b,a,t} \leq 1 \qquad \forall e \in E, b \in B, t \in T \qquad (19)$$

$$\sum_{a^{f}\in A} Y_{b,a,t} \leq 1 \qquad \forall f \in F, b \in B, t \in T \qquad (20)$$

Finally (21) and (22) are binary and non-negativity constraints of the model.

$$U_{r,s,b,t},\ U^{U}_{r,b,a,t},\ J^{C}_{e,b,t},\ P_{f,b,a,t},\ I^{B}_{f,b,t},\ P^{M}_{f,b,c,t},\ G_{e,b,a,t},\ G^{S}_{e,b,t},\ G^{U}_{e,b,t} \geq 0 \qquad \forall\, r \in R, s \in S, b \in B, a \in A, f \in F, c \in C, t \in T \qquad (21)$$

$$Y_{b,a,t},\ M_{f,c} \in \{0,1\} \qquad (22)$$

4.2. Robust Bioenergy Supply Network (RBE-SN) model

Costs, amount of resources, production, and the demand for bioenergy/biofuel products are considered as uncertain parameters. Then, by developing the DBE-SN model into its robust counterpart, these parameters are considered as random variables that acquire value from a symmetric distribution according to a nominal value. For instance, $\widetilde{\beta_{r,s,t}}$ belongs to the interval $\left[\beta_{r,s,t} - \widehat{\beta_{r,s,t}}, \beta_{r,s,t} + \widehat{\beta_{r,s,t}}\right]$, where $\beta_{r,s,t}$ is its nominal value and $\widehat{\beta_{r,s,t}}$ is the variation amplitude. Accordingly, the following robust method is proposed.

4.2.1. Objective function

The objective function presented in (1) is converted to (23) and (24). Since the model looks for the worst case, the whole expression (1) is considered equal to the maximum possible value (i.e. value of Z). Then, (1) is converted to the robust counterpart model presented in (23) to (31) by defining dual vectors $P^Z, a^1_{rsbt}, b^1_{rsbt}, c^1_{fbct}, d^1_{abt}, e^1_{rbat}, g^1_{ebt}, l^1_{fbt}$ and a budget parameter Γ^Z. It is worth mentioning here that Γ^Z acquires values in the range 0 to the sum of the number of uncertain parameters in (24).

$$Min\ Z \tag{23}$$

St:

$$\sum_{r\in R}\sum_{s\in S}\sum_{b\in B}\sum_{t\in T} \varsigma^{B}_{r,s,t} \cdot U_{r,s,b,t}$$

$$+\sum_{r\in R}\sum_{s\in S}\sum_{b\in B}\sum_{t\in T} \varsigma^{B,T}_{r,s,b,t} \cdot U_{r,s,b,t}$$

$$+\sum_{f\in F}\sum_{b\in B}\sum_{c\in C}\sum_{t\in T} \varsigma^{B,T}_{f,b,c,t} \cdot P^{M}_{f,b,c,t}$$

$$+\sum_{a\in A}\sum_{b\in B}\sum_{t\in T} \varsigma^{F}_{a,b,t} \cdot Y_{b,a,t}$$

$$+\sum_{r\in R}\sum_{b\in B}\sum_{a\in A}\sum_{t\in T} \varsigma^{V}_{b,a,t} \cdot U^{U}_{r,b,a,t}$$

$$+\sum_{e\in E}\sum_{b\in B}\sum_{t\in T} \varsigma^{E}_{e,b,t} \cdot J^{C}_{e,b,t}$$

$$+\sum_{f\in F}\sum_{b\in B}\sum_{t\in T} \varsigma^{H}_{f,b} \cdot I^{B}_{f,b,t}$$

$$+\sum_{r\in R}\sum_{s\in S}\sum_{b\in B}\sum_{t\in T} a^{1}_{r,s,b,t} + \sum_{r\in R}\sum_{s\in S}\sum_{b\in B}\sum_{t\in T} b^{1}_{r,s,b,t} + \sum_{f\in F}\sum_{b\in B}\sum_{c\in C}\sum_{t\in T} c^{1}_{f,b,c,t}$$

$$+\sum_{a\in A}\sum_{b\in B}\sum_{t\in T} d^1_{a,b,t} + \sum_{r\in R}\sum_{b\in B}\sum_{a\in A}\sum_{t\in T} e^1_{r,b,a,t} + \sum_{e\in E}\sum_{b\in B}\sum_{t\in T} g^1_{e,b,t}$$

$$+\sum_{f\in F}\sum_{b\in B}\sum_{t\in T} l^1_{f,b,t} + \Gamma^Z . P^Z \leq Z \tag{24}$$

$$P^Z + a^1_{r,s,b,t} \geq \widehat{\varsigma^B_{r,s,t}} \cdot U_{r,s,b,t} \qquad \forall r\in R, s\in S, b\in B, t\in T \tag{25}$$

$$P^Z + b^1_{r,s,b,t} \geq \widehat{\varsigma^{B,T}_{r,s,b,t}} \cdot U_{r,s,b,t} \qquad \forall r\in R, s\in S, b\in B, t\in T \tag{26}$$

$$P^Z + c^1_{f,b,c,t} \geq \widehat{\varsigma^{B,T}_{f,b,c,t}} \cdot P^M_{f,b,c,t} \qquad \forall f\in F, b\in B, c\in C, t\in T \tag{27}$$

$$P^Z + d^1_{a,b,t} \geq \widehat{\varsigma^F_{a,b,t}} \cdot Y_{b,a,t} \qquad \forall a\in A, b\in B, t\in T \tag{28}$$

$$P^Z + e^1_{r,b,a,t} \geq \widehat{\varsigma^V_{b,a,t}} \cdot U^U_{r,b,a,t} \qquad \forall r\in R, b\in B, a\in A, t\in T \tag{29}$$

$$P^Z + g^1_{e,b,t} \geq \widehat{\varsigma^E_{e,b,t}} \cdot J^C_{e,b,t} \qquad \forall e\in E, b\in B, t\in T \tag{30}$$

$$P^Z + l^1_{f,b,t} \geq \widehat{\varsigma^H_{f,b}} \cdot I^B_{f,b,t} \qquad \forall f\in F, b\in B, t\in T \tag{31}$$

4.2.2. Constraints:

According to Section 3.2 (Robust optimization approach) into each of the constraints (2), (9), (10), (13)–(14), and (17), the budget parameters are introduced, and these constraints are changed to constraints (32), (39), (40), (43)–(46), and (49), respectively. It can be observed that when perturbations are larger, these constraints become tighter.

$$\sum_{b\in B} U_{r,s,b,t} \leq \beta_{r,s,t} - \Gamma_{r,s,t} \cdot \widehat{\beta_{r,s,t}} \qquad \forall r\in R, s\in S, t\in T \tag{32}$$

$$\sum_{s\in S} U_{r,s,b,t} = \sum_{a\in A} U^U_{r,b,a,t} \qquad \forall r\in R, b\in B, t\in T \tag{33}$$

$$U^U_{r,b,a,t} \leq \varphi \cdot \psi_{r,a} \qquad \forall r\in R, b\in B, t\in T \tag{34}$$

$$P_{f,b,a,t} = \sum_{r\in R} \gamma_{f,r,a} \cdot U^U_{r,b,a,t} \qquad \forall f\in F, b\in B, a\in A, t\in T \tag{35}$$

$$G_{e,b,a,t} = \sum_{r\in R} \gamma_{e,r,a} \cdot U^U_{r,b,a,t} \qquad \forall e\in E, b\in B, a\in A, t\in T \tag{36}$$

$$P_{f,b,a,t} \leq \xi_{a,f}^{M} \cdot Y_{b,a,t} \qquad \forall f \in F, b \in B, a \in A, t \in T \qquad (37)$$

$$G_{e,b,a,t} \leq \xi_{a,e}^{M} \cdot Y_{b,a,t} \qquad \forall e \in E, b \in B, a \in A, t \in T \qquad (38)$$

$$P_{f,b,a,t} \geq \xi_{a,f}^{M} \cdot Y_{b,a,t} \cdot \mu_{f}^{m} + \Gamma_{f,b,a,t} \cdot \xi_{a,f}^{M} \cdot Y_{b,a,t} \cdot \widehat{\mu_{f}^{m}} \qquad \forall f \in F, b \in B, a \in A, t \in T \qquad (39)$$

$$G_{e,b,a,t} \geq \xi_{a,e}^{M} \cdot Y_{b,a,t} \cdot \mu_{e}^{m} + \Gamma_{e,b,a,t} \cdot \xi_{a,e}^{M} \cdot Y_{b,a,t} \cdot \widehat{\mu_{e}^{m}} \qquad \forall e \in E, b \in B, a \in A, t \in T \qquad (40)$$

$$\sum_{c \in C} P_{f,b,c,t}^{M} = \sum_{a \in A} P_{f,b,a,t} \qquad \forall b \in B, f \in F, t \in T \qquad (40)$$

$$G_{e,b,t}^{S} + G_{e,b,t}^{U} = \sum_{a \in A} G_{e,b,a,t} \qquad \forall e \in E, b \in B, t \in T \qquad (42)$$

$$\delta_{f,c,t}^{m} \cdot M_{f,c} + \Gamma_{f,c,t}^{1} \cdot \widehat{\delta_{f,c,t}^{m}} \cdot M_{f,c} \leq \sum_{b \in B} P_{f,b,c,t}^{M} \qquad \forall f \in F, c \in C, t \in T \qquad (43)$$

$$\sum_{b \in B} P_{f,b,c,t}^{M} \leq \delta_{f,c,t}^{M} \cdot M_{f,c} - \Gamma_{f,c,t}^{2} \cdot \widehat{\delta_{f,c,t}^{M}} \cdot M_{f,c} \qquad \forall f \in F, c \in C, t \in T \qquad (44)$$

$$\delta_{e,b,t}^{E,m} + \Gamma_{e,b,t}^{1} \cdot \widehat{\delta_{e,b,t}^{E,m}} \leq G_{e,b,t}^{S} \qquad \forall e \in E, b \in B, t \in T \qquad (45)$$

$$G_{e,b,t}^{S} \leq \delta_{e,b,t}^{E,M} - \Gamma_{e,b,t}^{2} \cdot \widehat{\delta_{e,b,t}^{E,M}} \qquad \forall e \in E, b \in B, t \in T \qquad (46)$$

$$\sum_{r \in R} \sum_{a \in A} \vartheta_{e,r,a}^{I,C} \cdot U_{r,b,a,t}^{U} = G_{e,b,t}^{U} + J_{e,b,t}^{C} \qquad \forall e \in E, b \in B, t \in T \qquad (47)$$

$$\sum_{a \in A} P_{f,b,a,t} + I_{f,b,(t-1)}^{B} \geq \sum_{c \in C} P_{f,b,c,t}^{M} + I_{f,b,t}^{B} \qquad \forall f \in F, b \in B, t \in T \qquad (48)$$

$$\sum_{b \in B} \sum_{c \in C} P_{f,b,c,t}^{M} \geq \varpi_{f,t}^{T} + \Gamma_{f,t} \cdot \widehat{\varpi_{f,t}^{T}} \qquad \forall f \in F, t \in T \qquad (49)$$

$$Y_{b,a,t} \geq Y_{b,a,(t-1)} \qquad \forall a \in A, b \in B, t \in T \qquad (50)$$

$$\sum_{a^{e} \in A} Y_{b,a,t} \leq 1 \qquad \forall e \in E, b \in B, t \in T \qquad (51)$$

$$\sum_{a^{f} \in A} Y_{b,a,t} \leq 1 \qquad \forall f \in F, b \in B, t \in T \qquad (52)$$

$$U_{r,s,b,t},\ U_{r,b,a,t}^{U},\ J_{e,b,t}^{C},\ P_{f,b,a,t},\ I_{f,b,t}^{B},\ P_{f,b,c,t}^{M},\ G_{e,b,a,t}, \qquad \forall r \in R, s \in S, b \in B, a \in A, f \in F, c \in C, e \in E, t \in T \qquad (53)$$

$G^S_{e,b,t}, G^U_{e,b,t} \geq 0$

$Y_{b,a,t}\ , M_{\ f,c} \in \{0,1\}$ (54)

$P^Z, a^1_{rsbt}, b^1_{rsbt}, c^1_{fbct}, d^1_{abt}\ , e^1_{rbat}, g^1_{ebt}, l^1_{fbt} \in R^+ \qquad \forall\, r \in R, s \in S, b \in B, a \in A,$ (55)

$f \in F, c \in C, e \in E, t \in T$

5. Case study

To illustrate how this approach can be used in practice, a case study from Iran is considered. Due to high climate diversity across the Iranian territory, there are many AF areas where the residues are left idle and sometimes incur costs and create environmental pollution for the inhabitants because the normal methods of disposal are burning or transportation to remote landfill sites.

Two main kinds of raw material (biomass) are considered for changing: 1) forest residues from operation processes in the forests and sawmill wastes such as chips, branches, shavings, leaves, sawdust, tree tops, hog fuel; 2) agricultural residues coming from grain harvesting of plants such as corn and wheat.

These residues can be changed to bioenergy like electricity and heat, be used to produce biofuel like ethanol, biodiesel, or converted to other products with a bio-base, e.g. plastics, and chemicals [7]. The basic processes for converting the biomass are thermochemical, biochemical, and chemical. The biochemical and thermochemical are appropriate methods for treating AF biomass, the former involves fermentation and hydrolysis and the latter involves pyrolysis, combustion, and gasification [10].

In this case study, the following four categories of the technologies for the biorefineries are considered: 1) gasification for producing heat and electricity; 2) combustion for producing heat and electricity; 3) generation of bio-oil through fast pyrolysis; and 4) pelletization, i.e. the production of pellets. Table 5 shows the different kinds of biomass needed for each technology [9, 61, 62]. Note that the processes of fast pyrolysis and combustion are able to convert all kinds of the biomass, in contrast, the processes of pelletization and gasification need biomass which is clean with low ash in content. Therefore, two kinds of the biomass can be used for the technologies of pelletization and gasification. These are the stem chips coming from harvesting residues of damaged mountain pines, and wood chips from sawmill waste [61, 63]. Four capacities (0.5, 2, 3, and 5 MW) are considered for the combustion technologies. Table 6 reports the efficiency of these technologies for the biorefineries [8, 64, 65]. Consulting the Renewable Energy and Energy Efficiency Organization (www.satba.gov.ir), for different capacities of burning technologies, there are a variety of electrical and thermal efficiencies. For pyrolysis technology at three capacities (200, 400, 600 ton/day), the efficiency depends on the type of biomass, see Table 5. For technology of pellet at three capacities (15000, 30000, 45000 ton/year), the efficiency is assumed to be 92%. [10, 65].

Table 5:

Biomass type and assigned technology							
				The biomass requirements (Particle size, Ash content, Moisture content) for assigned technology:			
	The biomass composition			Combustion technology (fixed bed)	Gasification technology (fixed bed)	Pyrolysis technology (fluidized bed)	Pellet technology
Biomass category	Bio-oil yield (m^3/ton)	Energy content (GJ/ton)	Biomass type	5–51mm <31% 11–51%	<76mm <7% <21%	<3mm Unknown <11%	<7mm <1% <11%
Sawmill wastes	0.494	17.83	Hog fuel	X		X	
	0.657	17.75	Wood chips	X	X	X	X
Harvesting residues	0.645	19.10	Chips from mountain pine beetle stems	X	X	X	X
	0.608	19.10	Hog fuel from harvesting residues	X		X	
Agricultural residues	0.618	19.80	Corn stover	X		X	
	0.616	19,65	Wheat straw	X		X	

Table 6

Efficiency of the technology		
	Efficiency (depends on the capacity)	
Biomass boiler + steam turbine(CHP)	14.5-18.5% Electrical	13-21.5% Thermal
Biomass boiler (heat only)	0.0% Electrical	70% Thermal
Biomass boiler + steam turbine (electricity only)	18% Electrical	0.0% Thermal
Biomass gasifier +ICE (CHP or electricity only)	12-21 % Electrical	8.5-10.5% Thermal
Biomass oil heater +ORC (CHP or electricity only)	11-12% Electrical	48-55 % Thermal

Four products, namely electricity, heat, bio-oil, and pellet are considered in this study: the electricity is either sold to the local electrical grid in the bio-refinery area or used inside the bio-refinery; heat is used both inside the bio-refinery and sold to the nearby factories/industries or houses around the bio-refinery area; bio-oil and pellets are stored to meet the local demand of the region as well as that from other regions or provinces.

Iran has a cross-country railroad network throughout most of the country and many highways and local roads. Since long-distance transportation is usually less expensive by train, most of the long-haul freight is transported to the railway station by trucks, from where it is transported by train to distant areas. Trucks usually travel at 70-80 km/hour while the train speed is about 60 km/hour. This case study used the expertise and GIS data from National Cartographic Center of Iran (www.ncc.ir), the national mapping agency, and also considered four 5-year periods.

6. Results and discussion

6.1. Results of the first phase of the proposed two-phase approach

The GIS data and the criteria/sub-criteria maps obtained from the national mapping agency were used as inputs for GIS software. Then, after digitalizing the maps, they were changed to the raster form (e.g. 95 m resolution). When this was achieved, a group of experts from the national mapping agency specializing in this field was asked to use the AHP method as a Multi-Criteria Decision Making (MCDM) technique to weight each map from an economic-engineering perspective.

According to [47], the map overlaying in a GIS is usually done either by the Boolean overlay method, which is applied to non-compensatory cumulative operators such as "union" (OR logic) with only one criterion and "intersection" (AND logic) with every criterion [66], or the weighted overlay method in which a relative importance weight is allocated to each evaluation criterion (or map layer) based on compensatory combinatorial rules. Hence, the weighted overlay method is more flexible than the Boolean method in selecting the appropriate locations of bio-refineries.

Table 7 shows the main types, the categories and the subcategories of different criteria and sub-criteria used in the decision-making problem considered in this study. They are considered as a descending hierarchical structure. Four main category types (societal, resource, economic, and environmental) are considered at the upper level, subdivided into eight categories, and then the sub-categories are considered for the next level of the descending hierarchical structure. For each level of this hierarchy, the paired comparison matrix is computed by the experts (e.g. from National Cartographic Center of Iran; www.ncc.ir). For example, in the third row of Table 7, the economic criteria are divided into distance to the road and distance to the rail. In the experts' opinion, these two criteria can be divided into five sub-criteria (i.e. 0-3, 3-6, 6-20, 20-50, 50-100 km for distance to the road, and 0-5, 5-10, 10-25, 25-45, 45-100 km for distance to the rail). Using AHP, their weights can be obtained. Table 7 shows that all consistency ratios (CR) obtained from the weights are less than 0.1, this indicates the consistency of the formed matrix and the reliability of the calculated weights.

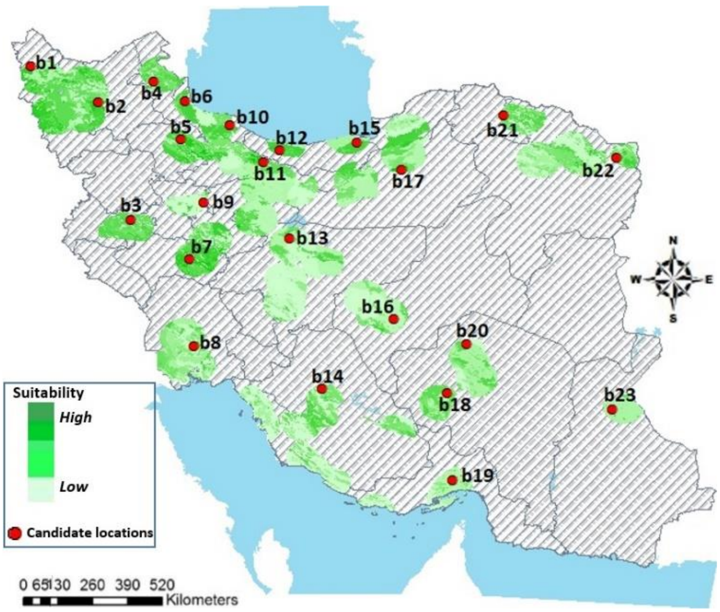

Figure 3: Final map of suitable locations for the selection of bio-refinery sites

Table 7:

The weights of main categories, categories and sub-categories for choosing the bio-refineries' location								
Main category	*W*	*CR*	*Category*	*W*	*CR*	*Sub-category*	*W*	*CR*
Social criteria	0.3323	0.0043	Distance to the areas with high rate of unemployment (km).	0.5432	0.0134	0-1.5	0.3134	0.0446
						1.5-4.5	0.2439	
						4.5-17	0.1897	
						17-70	0.1447	
						70-100	0.1083	
			Distance to the areas with high vulnerability	0.4568		0-1.5	0.3456	0.0533
						1.5-4.5	0.2676	
						4.5-17	0.1955	
						17-70	0.1467	
						70-100	0.0446	
Resource criteria	0.3226		Distance to procurement centers/ forest products mills	0.5113	0.0673	0-3	0.3236	0.0674
						3-12	0.2246	
						12-25	0.1954	
						25-75	0.1632	
						75-100	0.0932	
			Distance to power plant (km)	0.4887		0-1.5	0.3238	0.0521
						1.5-4.5	0.2576	
						4.5-17	0.1964	
						17-70	0.1359	
						70-100	0.0863	
Economic criteria	0.2130		Distance to road (km)	0.4385	0.0062	0-3	0.3261	0.0102
						3-6	0.2631	
						6-20	0.1877	
						20-50	0.1346	
						50-100	0.0885	
			Distance to rail (km)	0.5615		0-5	0.3417	0.0143
						5-10	0.2736	
						10-25	0.1917	
						25-45	0.1114	
						45-100	0.0816	
Environmental criteria	0.1321		Land use	0.5026	0.0324	Barren land	0.2646	0.0443
						Pasture	0.1825	
						Herbaceous	0.1729	
						Shrub	0.1836	
						woodland	0.1964	
			Slope	0.4974		1°	0.3554	0.0621
						2°	0.2411	
						3°	0.1613	
						4°	0.1321	
						5°	0.1101	

All the digital map layers are weighted by using the weights computed in Table 7 and are combined with the GIS analyzer. The final map for the proposed locations is calculated using the suitability index. The map is presented in Figure 3. Finally, 23 candidate locations with a high-suitability level are selected by using the equal-distance classification method. These suitable locations are considered as inputs for the second phase.

6.2. Results of the second phase

For this part of case study, both the proposed MILP models were coded in GAMS 24, and solved by using the CPLEX solver. All empirical experiments were implemented with an Intel Core i3, 2.13 GHz processor with 4GB of RAM. The robust model's efficiency and performance were examined and compared with the deterministic model.

6.2.1. Effects of uncertainty on total costs of the bioenergy SC

The uncertainty's effect on the total SC costs is examined by changing the robust model's conservatism level and the perturbation amplitude of uncertain parameters. Levels considered for the perturbation amplitude ($\widehat{a_{ij}}$) are 5, 10, 20 and 30% and those for the reliability and conservatism levels, controlled by the budget parameter Γ, are 68, 83, and 99%. Table 8 presents the different results obtained by adjusting each perturbation amplitude/reliability level of the model. It can be seen that the robust model costs are higher than the deterministic one at all uncertainty levels, due to the increase in the costs of improving the bioenergy SC stability. This increase becomes more significant as the conservatism/perturbation level increases. For instance, at high conservatism and risk aversion levels of the model (99% reliability and 30% amplitude), the total SC cost increases by 49.3% compared to the deterministic case. At lower uncertainty levels, it is possible, of course, to pay more reasonable costs, by creating a trade-off between robustness and the corresponding cost.

Table 8:

The models' total cost($M)					
	Robust				Deterministic
Conservatism	perturbation				637.5
	5%	10%	20%	30%	
68%	639.1	662.2	708.3	772.7	
83%	658.4	683.9	735.2	826.4	
99%	696.5	731.7	802.3	951.8	

Examining and comparing the problem solution times is another outcome of solving the robust model with different conservatism/risk levels. As shown in Table 9, although the new constraints and variables are defined in the model (robust), it is still tractable from computational point of view, and the techniques used prevents elongation of the solution time compared with the deterministic model.

Table 9:

The models' computational time (s)					
	Robust				Deterministic
Conservatism	perturbation				598.3
	5%	10%	20%	30%	
68%	686.9	688.2	690.9	625.9	
83%	628.2	654.5	601.9	642.1	
99%	640.1	666.3	613.8	654.5	

To study the differences in the costs of the deterministic and robust models, we first study each set of uncertain parameters at different perturbation and conservatism levels, and then check the effects on the increase in the total cost of the bioenergy SC by examining the normalized deviation, i.e.,

$(Z - Min\ Total\ Cost)/Min\ Total\ Cost$

where Z and $Min\,Total\,Cost$ are the optimum values of the robust and deterministic models, respectively.

Figures 4 to 8 show the values of the responses to various perturbations and uncertainties. At 30% perturbation, changes in the data of the biomass accessibility and transportation costs of the SC lead to increases of about 3.75% and 2.35%, respectively, in the total SC cost, while changes in the demand data, bio-refinery investment costs, and operation costs of conversion technologies would each increase the total SC cost by 5.1%, 9.3%, and 11%, respectively. These results suggest that efforts should be made to estimate the bio-refinery investment costs and the operation costs of conversion technologies more accurately.

Another point worth mentioning here is that, as shown in the demand graph (Figure 4), if the reliability is enhanced, the change in the total cost reaches its worst value more rapidly, while in Figures 5 to 8, the worsening rates enhance more slowly (gradually). This means that the change in the total cost shows a strong reaction to changes in the demand data, even at a low conservatism level. Hence, it is necessary that the demand data uncertainty be examined precisely, even regarding a risk-taking decision-maker who usually accepts a relatively high level for violation of the constraints.

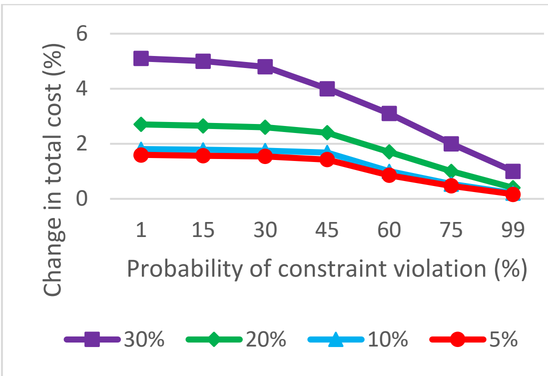

Figure 4: Bioenergy SC cost response to demand data variations

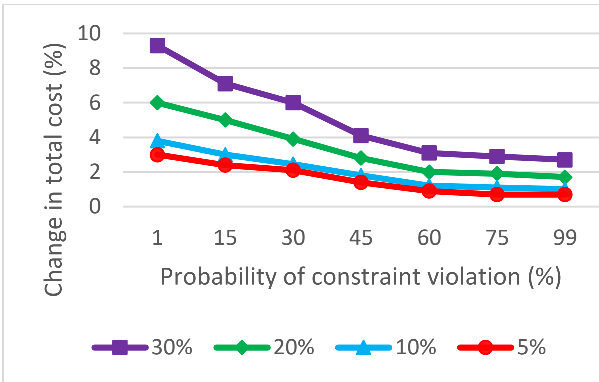

Figure 5: Bioenergy SC cost response to bio-refinery investment cost data variations

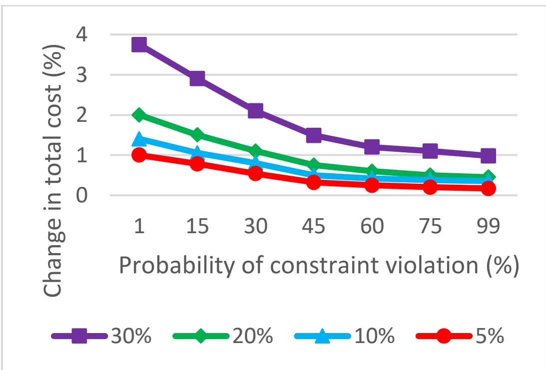

Figure 6: Bioenergy SC cost response to biomass accessibility data variations

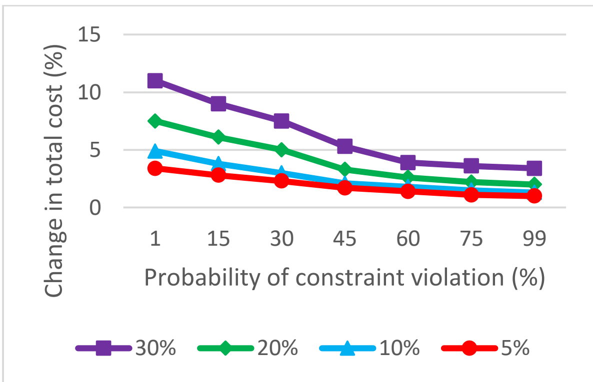

Figure 7: Bioenergy SC cost response to conversion technologies' operating cost data variations

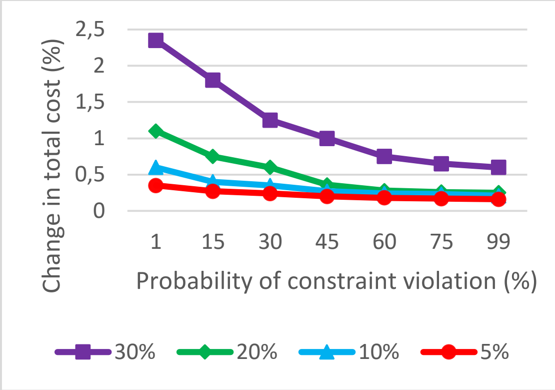

Figure 8: Bioenergy SC cost response to transportation cost data variations.

6.2.2. Effects of uncertainty on the bioenergy SC structure

Figures 9-13 and Table 10 report the optimal designs obtained by the two models (Robust and Deterministic) for 4 data perturbation levels. Figures 9-13 show that both models suggest almost identical locations for bio-refineries meaning that the strategic location decisions are reasonably robust and do not become invalid due to small data noise. In contrast, they perform differently in determining the type of conversion technologies and their capacities inside bio-refineries. In general, the robust approach creates a greater number of facilities (a spread form) or a lower number of higher-capacity facilities (centralized configuration) comparing the deterministic approach, so that the system can satisfy all (most) of the constraints in the worst scenarios [54]. For the specific SC in this study, the robust approach suggests fewer, but higher capacity facilities. This is shown in Figures 12 and 13 where bio-refineries b_{15} and b_{16} are eliminated.

Table 10 shows that in the biorefinery areas b2, b8-b10, b12-b14, b19 and b21 at least one technology is installed under both the deterministic and robust models. Only location b15 is not selected for any technology under the robust model with 20% perturbation, and locations b15 and b16 are not selected for any technology under the robust model with 30% perturbation; other locations are identical (in the deterministic and robust models). This means that if there is small data noise, the strategic decisions related to the biorefineries locations where the technologies are installed will not be invalidated, and they are reasonably robust against the uncertainty. On the other hand, Table 10 shows that, under uncertainty, different technologies as well as various capacities are selected. For example, in location b2 the robust model under 20% perturbation suggests installing the technology to produce pellets with a capacity of 30,000 t/year while the deterministic model suggests the same technology but different capacity (15,000 t/year).

Similarly, the deterministic model suggests installing the biomass boiler and steam turbine with 3MW capacity in location b10, but the robust model, under 20% perturbation, suggests a different technology (pellet 45,000 t/y). In Table 10, the robust model suggests equal to or higher than the capacity of each technology proposed with the deterministic model (e.g. under perturbation 30%, the robust model suggests a pellet plant at 30,000 instead of 15,000 t/year suggested by the deterministic model in b2). However, the total number of technologies is reduced when the robust model is used (e.g. the robust model under 30% perturbation suggests 14 technologies, instead of 20 technologies suggested by the deterministic model). Compared with the deterministic model, the robust model in this study tends to a centralized configuration (a lower number of higher-capacity facilities), so the system can satisfy all (most) of the constraints in the worst scenarios [54]. The reason can be understood better by looking at Figures 5 and 7. These figures show that the changes in data of the bio-refinery's investment cost and the operation cost of the conversion technology significantly affect the objective function of the model. Therefore, the robust model tries to weaken this undesirable impact by offering fewer bio-refineries with higher technological capacities (due to their more affordable economic scale). It is worth mentioning that when the technological capacity increases, the variable production cost decreases relative to the total production.

In addition, Figures 9-13 demonstrate that the bio-oil and pellet demands are satisfied with, respectively, three yellow and green colors (pale to dark). The point is that the provinces selected as pilot markets are not equal, whether for products in the deterministic and robust models or for their demands. However, 5 provinces (C_1 to C_5 in Figure 9) appear as optimal markets in all cases, and since they stay optimal even with data perturbation, they can be considered as reliable options in the early steps of the development process in the biofuel market.

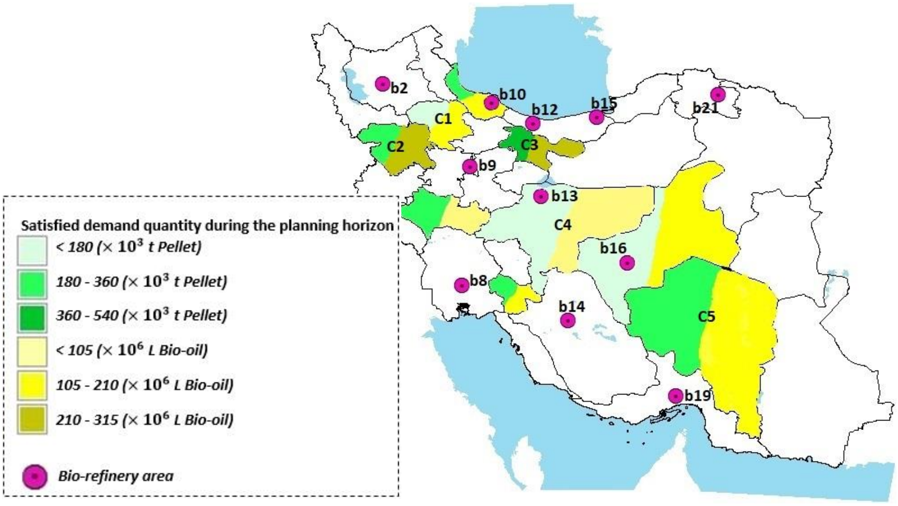

Figure 9: Deterministic model

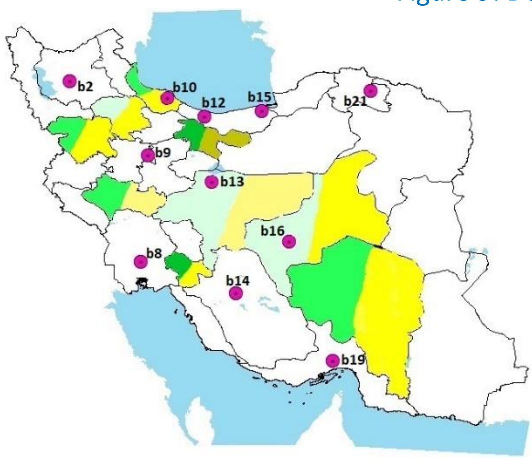

Figure 10: Robust model (with 99% reliability and 5% perturbation)

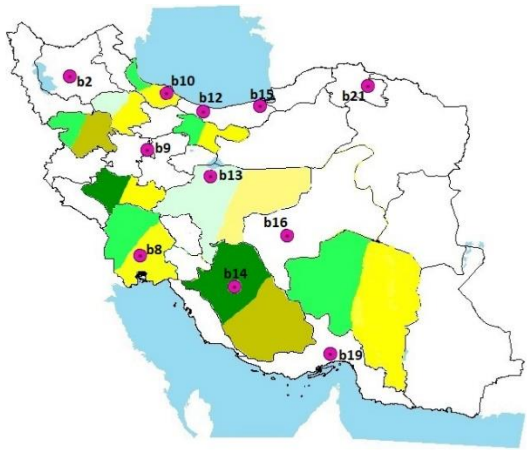

Figure 11: Robust model (with 99% reliability and 10% perturbation)

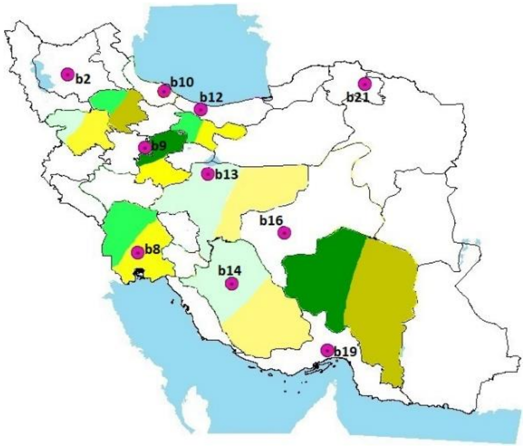

Figure 12: Robust model (with 99% reliability and 20% perturbation)

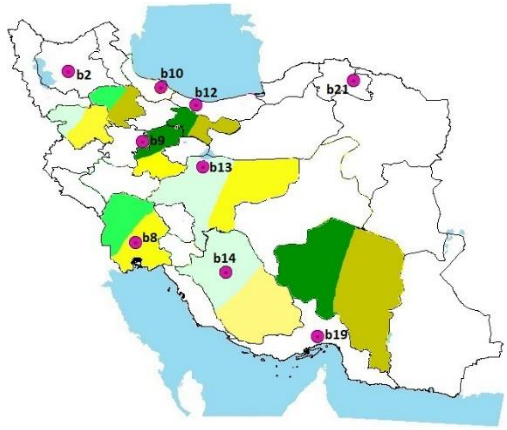

Figure 13: Robust model (with 99% reliability and 30% perturbation)

6.2.3. Sensitivity analysis

Here the effects of the following critical parameters on the total cost are evaluated by sensitivity analysis: (*a*) biomass cost; (*b*) biomass availability; (*c*) bio-oil demand; (*d*) capital costs; (*e*) technology conversion yield; (*f*) production costs; (*g*) heat demand, and (*h*) transportation cost of biofuel.

The sensitivity is performed using the following conditions: reliability and perturbation level are set to 99% and 30% respectively (base case model), and then nominal values of the 8 parameters are changed over reasonable ranges ($\pm 20\%$). Figure 14 reports the sensitivity analysis results. It shows that the total cost is very sensitive to the costs of investment and production. If the capital costs and production costs are increased by $+20\%$, for each of the costs, the total cost increases by more than 44% and 42% respectively.

As shown in Figure 14, the conversion technology's transformation yields have a greater effect on the total cost in negative changes than positive ones. The biomass mix in the base case model is often made of forest and sawmill residues. If the transformation yield of the conversion technology is enhanced to 20%, the use of forest residues is reduced, which means the cost of biomass will have a proportional reduction. Nevertheless, if the transformation yield decreases by 20%, more wheat straw and corn stover (residues of agriculture) have to be supplied, and these cost more than forest residues. Consequently, the total cost increases by more than 32%.

In addition, when there are variations in demand for bio-oil, the change of total cost can vary approximately in a range from -14% to +13%. The investigation indicates that when demand of bio-oil rises to 20%, this leads to a centralized configuration in which one larger pyrolysis plant (600 ton/day) is installed in location b9 instead of the two smaller pyrolysis plants (one 200 ton/day in location b10, and one 200 ton/day in location b9) in the base case model, see Figure 13 and the last column of Table 10. This reduces the total cost.

Moreover, the total cost changes of the bioenergy SC are proportional to the changes in the biomass cost, and the total cost of the supply chain is relatively insensitive to variations in other parameters like the availability of biomass, heat demand and the cost of transportation.

Table 10:

Optimal designs of the bioenergy SC, reliability = 99%					
Technologies	**Deterministic model**	**Robust model (perturbation 5%)**	**Robust model (perturbation 10%)**	**Robust model (perturbation 20%)**	**Robust model (perturbation 30%)**
b2					
Steam turbine &biomass boiler (electricity only),(MW)	5				
pellet plant, (t/year)	15000	15000	15000	30000	30000
pyrolysis plant, (t/day)	200	200	200		
b8					
steam turbine &biomass boiler & (CHP), (MW)	0.5	2	3	5	5
pellet plant, (t/year)					
pyrolysis plant, (t/day)	400	400	400		
b9					
ORC & biomass oil heater (CHP or electricity only), (MW)	2	3	3	5	5
pellet plant, (t/year)	15000	15000	15000		
pyrolysis plant, (t/day)				200	200
b10					
Steam turbine & biomass boiler (CHP), (MW)	3	3	5		
pellet plant, (t/year)				45000	
pyrolysis plant, (t/day)					200
b12					
ICE & biomass gasifier (CHP or electricity only) (MW)	0.5	2	3	5	5
pellet plant, (t/year)				45000	45000
pyrolysis plant, (t/day)	400	400	400		
b13					
Steam turbine& biomass boiler (CHP), (MW)	2	3	3	5	
pellet plant, (t/year)	15000	45000	45000	45000	45000
pyrolysis plant, (t/day)				600	600
b14					
Steam turbine & biomass boiler (CHP), (MW)	5	5	5	5	5
pellet plant, (t/year)					
pyrolysis plant, (t/day)					600
b15					
Biomass boiler (heat only)(, (MW)	0.5	2	3		
pellet plant, (t/year)					
pyrolysis plant, (t/day)	400	400	400		
b16					
Steam turbine & biomass boiler (CHP), (MW)	2	3	3	2	
pellet plant, (t/year)	15000	15000	15000	45000	
pyrolysis plant, (t/day)					
b19					
Steam turbine& biomass boiler (CHP), (MW)	5	5	5	5	5
pellet plant, (t/year)					
pyrolysis plant, (t/day)					
b21					
ORC & biomass oil heater (CHP or electricity only), (MW)	0.5	2	3	5	5
pellet plant, (t/year)					45000
pyrolysis plant, (t/day)	400	400	400		
Total number of technologies	20	19	19	15	14

ICE: Internal combustion engine, ORC: Organic rankine cycle, CHP: Combined heat and power.

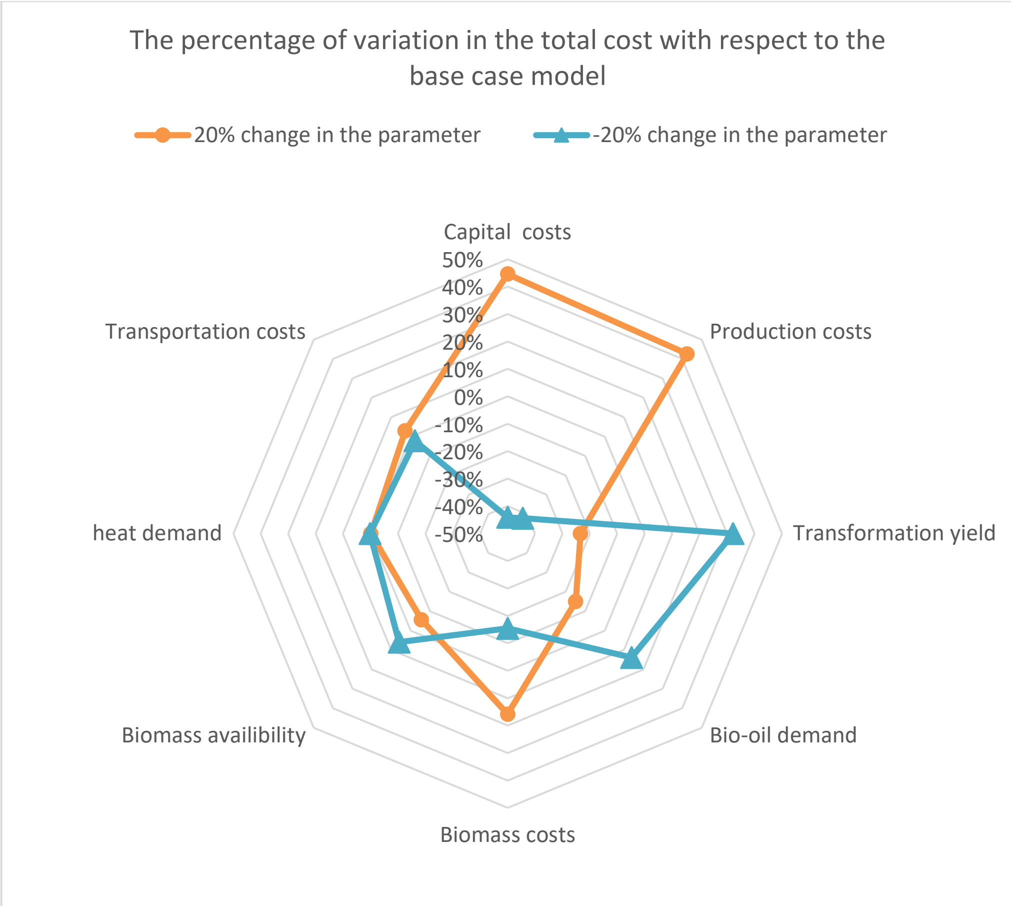

Figure 14: Sensitivity analysis under robust model (with respect to the base case model: perturbation= 30%, reliability =99%).

6.2.4. The social effects of the bioenergy SC on the territories

In this section, the effect of the bioenergy supply chain on the society in the territories where bio-refineries are established, is investigated. To do so, we define the social profit of creating job *w* (the work hours) in territory *b* as follows:

$$\boldsymbol{Social\ profit_{w,b} = \Psi_{w,b} \times The\ required\ hours_{w,b}\ (Hourly\ wage\ work + Salaried\ work)} \quad \text{(S2)}$$

Where hourly wage work refers to the work involved in transforming the biomass to bioenergy and biofuel, and salaried work refers to the work of keeping the bio-refinery open (jobs with a fixed salary). The work hours needed to convert the biomass using the different technologies can vary depending on the capacities. Table 11 shows the assumptions related to the work (hours of work) for the different technologies of combustion, pellet and pyrolysis. The total requested jobs (in terms of whole hours needed for work) for the different types of technologies with the different capacities come from the reports presented in [65, 67], and from consultation with the Renewable Energy and Energy Efficiency Organization (www.satba.gov.ir). In addition, the work (the work hours) requested for technologies related to pyrolysis and pellet with different capacities, hourly-wage work, and salaried work hours also come from different previous studies [9, 61, 68].

Table 11:

Work hours (per year) needed for working with different technologies.						
Kinds of technology	**Hours needed for each job class**					
	Salaried work			**Hourly-wage work**		
	combustion	**pellets**	**pyrolysis**	**combustion**	**pellets**	**pyrolysis**
pyrolysis (200 t/day)	-	-	10222	-	-	16422
pyrolysis (400 t/day)	-	-	10222	-	-	16602
pyrolysis (600 t/day)	-	-	10222	-	-	16802
pelletizing (15000 t/ year)	-	10222	-	-	26899	-
pelletizing (30000 t/ year)	-	10222	-	-	27902	-
pelletizing (45000 t/ year)	-	10222	-	-	30152	-
Biomass boiler (heat only)(0.5MW)	2812	-	-	17000	-	-
Biomass boiler (heat only)(2MW)	2812	-	-	17102	-	-
Biomass boiler (heat only)(3MW)	2812	-	-	17102	-	-
Biomass boiler + steam turbine (CHP) (0.5MW)	3151	-	-	17122	-	-
Biomass boiler + steam turbine (CHP) (2MW)	3151	-	-	17143	-	-
Biomass boiler + steam turbine (CHP) (3MW)	3151	-	-	17152	-	-
Biomass boiler + steam turbine (CHP) (5MW)	3151	-	-	17252	-	-
Biomass boiler + steam turbine (electricity only) (0.5MW)	3031	-	-	16226	-	-
Biomass boiler + steam turbine (electricity only) (2MW)	3031	-	-	17126	-	-
Biomass boiler + steam turbine (electricity only) (3MW)	3131	-	-	17226	-	-
Biomass boiler + steam turbine (electricity only) (5MW)	3145	-	-	17243	-	-
Biomass oil heater + ORC(CHP or electricity only)(0.5MW)	2826	-	-	16122	-	-
Biomass oil heater + ORC(CHP or electricity only)(2MW)	2826	-	-	17122	-	-
Biomass oil heater + ORC(CHP or electricity only)(3MW)	2826	-	-	17222	-	-
Biomass oil heater + ORC(CHP or electricity only)(5MW)	2826	-	-	17322	-	-
Biomass gasifier + ICE (CHP or electricity only)(0.5MW)	3156	-	-	16000	-	-
Biomass gasifier + ICE (CHP or electricity only)(2MW)	3156	-	-	17057	-	-
Biomass gasifier + ICE (CHP or electricity only)(3MW)	3156	-	-	17157	-	-
Biomass gasifier + ICE (CHP or electricity only)(5MW)	3156	-	-	17257	-	-

The social profits obtained from the optimal design of the bioenergy supply chain (by using the deterministic and robust models with 99% reliability level) are calculated and presented in Table 12 (using Table 10, Table 11 and equation (S2)). In order to obtain the number of jobs, value 1 is substituted instead of the social impact ($\Psi_{w,b}$) in (S2). Table 12 shows the social profit generated by the optimal design (considering Table 10) obtained with the deterministic model and robust model with 99% reliability and 5%, 10%, 20%, 30% perturbation. Considering the last row of Table 12, the maximum social profit and created jobs belong to the deterministic model (48.84 M points and 263 jobs respectively), and the minimum belongs to the robust model under 30% perturbation. As mentioned in Section 6.2.2, in this case, comparing the deterministic model, the robust model tends to give a centralized configuration (a lower number of higher-capacity facilities). Therefore, fewer work hours are created in the robust design under 30% perturbation compared with the deterministic model. The robust model under 99% reliability and 30% perturbation designs a supply chain giving social benefit (up to 31.79 M points) and 171 jobs. Table 12 shows that at lower perturbation levels, it is of course possible, to have more social profit and jobs. If the robust model with 10% perturbation and 99% reliability is considered, it leads to the creation of social benefit (up to 45.89 M points) and 262 jobs under uncertain conditions. These jobs are created in the areas with high rates of unemployment and high vulnerability to the variation in the markets in an economic crisis, so the jobs have a very significant impact on the local society.

Table 12: Social profit and number of jobs made by installed technologies (reliability:99%)

Technologies	**Deterministic model**	**Robust model (perturbation 5%)**	**Robust model (perturbation 10%)**	**Robust model (perturbation 20%)**	**Robust model (perturbation 30%)**
b2					
Biomass boiler + steam turbine (electricity only),(MW)	2839070				
pellet plant, (t/year)	3014968	3014968	3014968	3096431	3096431
pyrolysis plant, (t/day)	4080262	4080262	4080262		
b8					
Biomass boiler + steam turbine (CHP), (MW)	2413257	2415757	2416829	2428732	2428732
pellet plant, (t/year)					
pyrolysis plant, (t/day)	3511530	3511530	3511530		
b9					
Biomass oil heater + ORC(CHP or electricity only), (MW)	2240160	2251390	2251390	2262620	2262620
pellet plant, (t/year)	2431426	2431426	2431426		
pyrolysis plant, (t/day)				3290534	3290534
b10					
Biomass boiler + steam turbine (CHP), (MW)	1960823	1960823	1960823		
pellet plant, (t/year)				2274267	
pyrolysis plant, (t/day)					2829859
b12					
Biomass gasifier + ICE (CHP or electricity only) (MW)	1807024	1906733	1916166	1925599	1925599
pellet plant, (t/year)				2221377	2221377
pyrolysis plant, (t/day)	2782722	2782722	2221377		
b13					
Biomass boiler + steam turbine (CHP), (MW)	2005534	2006424	2006424	1924656	
pellet plant, (t/year)	2139654	2327157	2327157	2327157	
pyrolysis plant, (t/day)				2936968	2936968
b14					
Biomass boiler + steam turbine (CHP), (MW)	2199607	2199607	2199607	2199607	2199607
pellet plant, (t/year)					
pyrolysis plant, (t/day)					3203965
b15					
Biomass boiler (heat only)(, (MW)	1334933	1341805	1341805		
pellet plant, (t/year)					
pyrolysis plant, (t/day)	1987658	1987658	1987658		
b16					
Biomass boiler + steam turbine (CHP), (MW)	1868793	1869622	1869622	1869622	
pellet plant, (t/year)	1993769	1993769	1993769	2168488	
pyrolysis plant, (t/day)					
b19					
Biomass boiler + steam turbine (CHP), (MW)	2245432	2245432	2245432	2245432	
pellet plant, (t/year)					
pyrolysis plant, (t/day)					
b21					
Biomass oil heater + ORC(CHP or electricity only), (MW)	2340646	2464176	2476529	2488882	2488882
pellet plant, (t/year)					2908947
pyrolysis plant, (t/day)	3644040	3644040	3644040		
Total social profit (M points)	48.84	46.43	45.89	35.66	31.79
Total number of Jobs (Jobs)	263	255	262	217	171

6.3. The performance analysis

In order to show the advantage of the suggested approach and model compared with conventional ones some tests are implemented here.

In type 1 tests, instead of using the locations introduced by the first phase, some arbitrarily chosen locations are used (three diverse sets). A basic case mode, reliability 99% and perturbation 30%, is considered for the robust model, which is then run. The total cost of the bioenergy supply chain and time of the computations are considered to evaluate the performance, see Figure 15.

Figure 15 shows if the robust model is employed, the cost is smaller (as well as the computational time) for the case of high-suitability candidate locations, than for arbitrarily chosen candidate locations used. If 23 arbitrary chosen candidate locations are selected, this increases the total bioenergy SC cost to 1361M$ (42% more than the optimal cost). Figure 15 also shows that when 33 or 43 arbitrary chosen candidate locations are considered, although the total bioenergy SC cost is reduced compared with 23 arbitrary chosen candidate locations, the computation time increases significantly. Furthermore, when more candidate locations are used, it does not necessarily mean that it is possible to build a bio-refinery in a feasible region while meeting all the environmental, economic, social, and technological constraints. Thus, the first phase of the proposed approach which selects the candidate locations to build bio-refineries with high suitability ranking, increases both the performance as well as the tractability of the bioenergy supply chain design model.

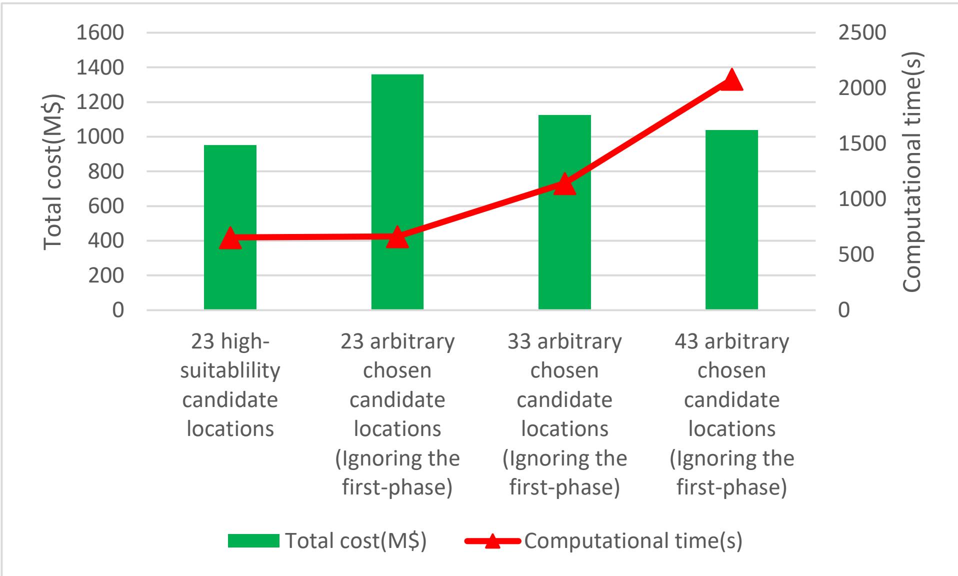

Figure 15: Effects of using the locations introduced by the first phase vs. ignoring the first phase

In type 2 tests, in order to investigate the desirability and robustness of both models, 55 random realizations are generated, for each perturbation level, by using a uniform distribution inside of the perturbation intervals (the extreme points) of uncertain parameters, then substituted in (1) to (22). The compact form of the realization-based model is as follows:

$$Min\ obj = F_{real}x^* + C_{real}y^* + \sum_i \xi R_i$$

st: (56)

$$A_{real,i}x^* + B_{real,i}y^* + R_i \geq D_{real,i}$$

In this model, capital letters represent the realized values, x^* and y^* are respectively the values of the integer and continuous variables generated optimally by the two models. The decision variable R_i measures the violation of constraints caused by the infeasible solution (x^*, y^*) and ξ is its penalty. Then the mean values and standard deviations obtained from the objective function of the model (56) are calculated and presented in Figures 16 to 18.

The mean value indicates the model (robust) performs better than the deterministic one, for every case of different perturbation and reliability levels, and this superiority is more important when the perturbation level is increased meaning that when the supply chain suffers from insufficient historical data, the model (robust) is coordinated more effective with it, especially in greater levels of perturbation.

Results also show that when the conservatism level increases, the distance between the performances of the two approaches increases as well. In fact, one advantage of the robust solution is that at different possible values for uncertain parameters, it stays feasible with a cost increase. Consequently, here in this particular case, the preferred option is the biggest values for reliability and perturbation levels, which offers greater safety and immunity. Nevertheless, 30% perturbation and 99% reliability may not be the best option, the final decision depends on the level of acceptability of the risk by the decision-maker. As shown in Figures 16 to 18, the deterministic model's standard deviations are much larger than the model (robust). It means when the parameters are affected by small perturbation, the solution coming from the deterministic model has deviated considerably but the solutions of the model (robust) stay close to the optimal solution.

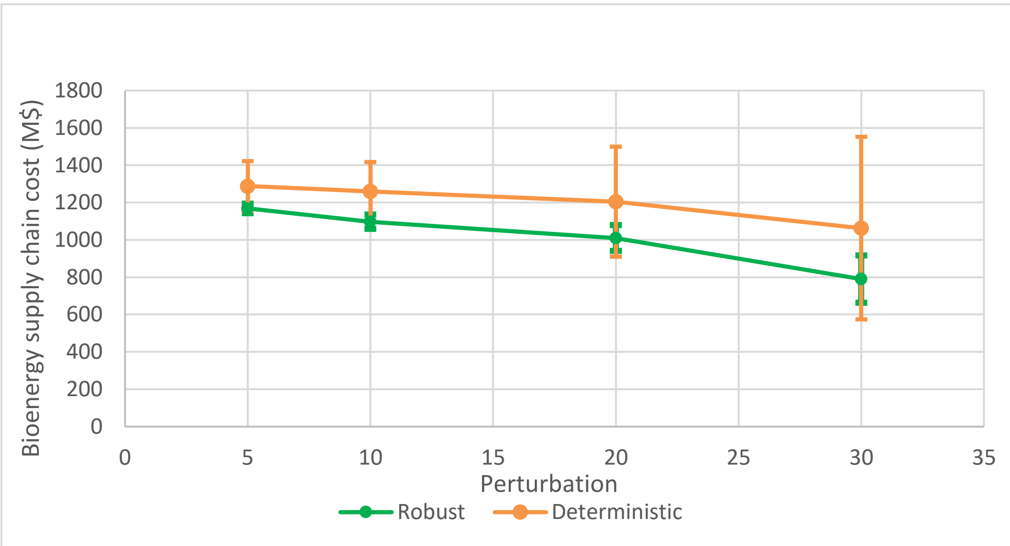

Figure 16: The two models' performance (68% reliability)

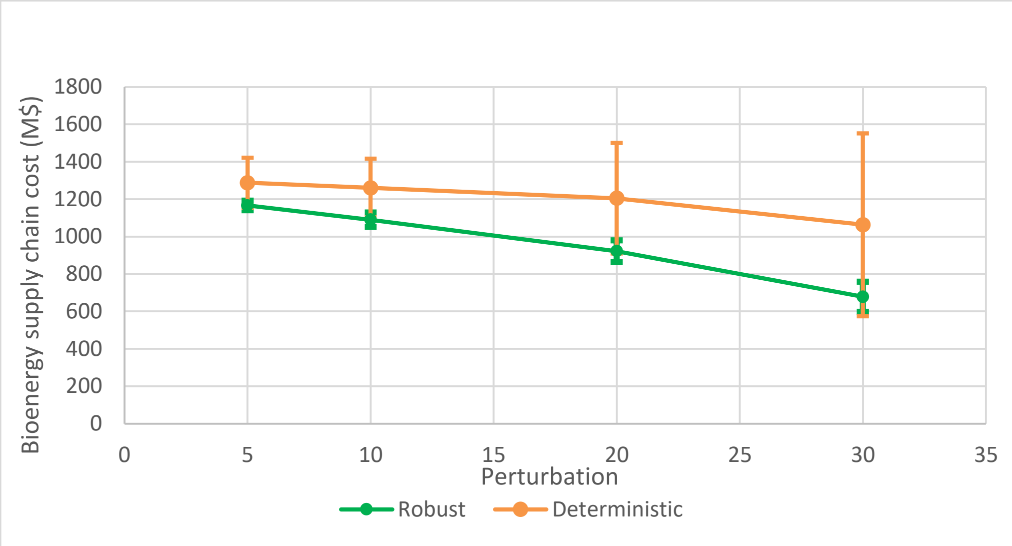

Figure 17: The two models' performance (83% reliability)

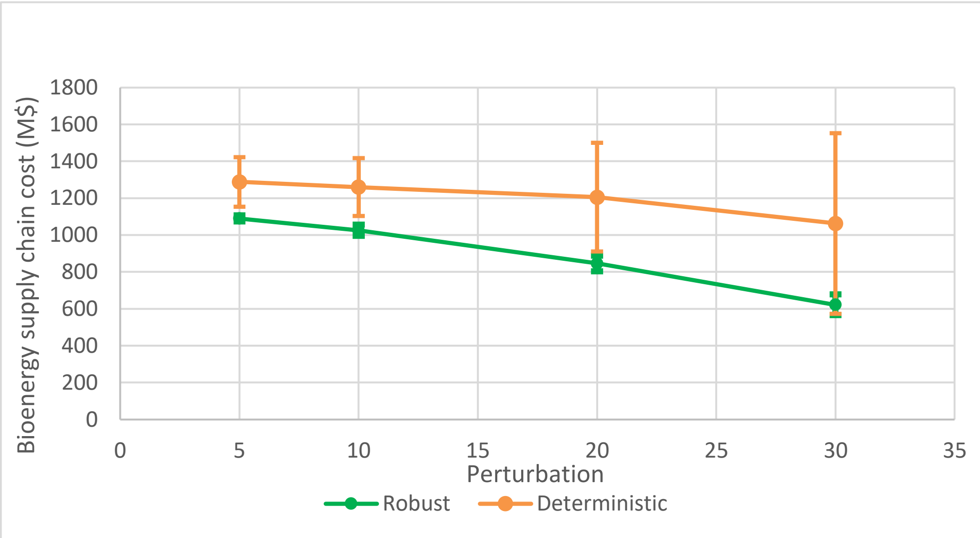

Figure 18: The two models' performance (99% reliability)

7. Conclusions

In this paper, a two-phase approach was proposed in order to design bioenergy SCs. The first phase, by integrating geographical information, social aspects, and by using multi-criteria decision-making techniques, aimed to find the appropriate locations for the bio-refineries in a geographical area. High rates of unemployment and high vulnerability of the territtories to variations in the markets during an economic crisis are considered as social concerns. The first phase enhances the practicality of the supply chain design, reduces its computational complexity, and help set up a sustainable development. The selected locations serve as input for the second phase. In the second phase, in order to cope with the uncertainties, a robust model is used to reduce the sensitivity to inaccurate input data. The use of the robust model leads to solutions which stay optimal, even when the parameters change slightly. In order to validate the two-phase sequential approach, a case study was carried out which showed that the proposed approach outperformed the traditional models, and for the case considered, led to creating 262 jobs. The jobs will be created in the areas with high rates of unemployment, and high vulnerability, so the jobs have a significant impact on the local society.

This work can be expanded in various ways. In future research, firstly, additional decisions could be integrated into the SC design: for instance, the new model could include some supplementary costs in order to provide insurance for the bio-refinery workers. Secondly, initial capacities or high technologies could be considered to improve the conversion productivity. Thirdly, product recycling after use by the customer can be considered. Fourth, decisions related to carbon trading and carbon pricing policies can be used. Finally, a column-wise version of the robust optimization can be used in order to tackle uncertainty better [69].

Appendix

Table 2: Interpretation of parameters, sets, and variables	
Set	Definition
R	Set of biomass feedstock types (raw materials); index $r \in R$
S	Set of biomass supply sources (forests/agricultural lands); index $s \in S$
B	Set of bio-refineries' candidate locations; index $b \in B$
A	Set of biomass conversion technologies; index $a \in A$
C	Set of biofuels' candidate markets; index $c \in C$
F	Set of various biofuels (bio-oils or condensed products) shipped to biofuel markets; index $f \in F$
E	Set of various bioenergy types (heat, electricity) used/sold at bio-refineries; index $e \in E$
T	Set of periods; index $t \in T$
Parameter	
$\widetilde{\beta_{r,s,t}}$	Various biomass types r available at supply source s in period t (ton)
$\gamma_{e,r,a}$	Type e bioenergy produced from 1 unit type r biomass by technology a (product output/1 ton biomass input)
$\gamma_{f,r,a}$	Type f biofuel produced from 1 unit type r biomass by technology a (product output/1 ton biomass input)
$\widetilde{\delta_{e,b,t}^{E,M}}$	Max. amount of external demand for type e bioenergy required at location b during period t (MWh of bioenergy)
$\widetilde{\delta_{e,b,t}^{E,m}}$	Min. amount of external demand for type e bioenergy required at location b during period t (MWh of bioenergy)
$\vartheta_{e,r,a}^{I,C}$	Internal demand for bioenergy type e required to convert 1 unit biomass type r using technology a
$\widetilde{\delta_{f,c,t}^{M}}$	Max. amount of market c demand for biofuel f during period t (units of product)
$\widetilde{\delta_{f,c,t}^{m}}$	Min. amount of market c demand for biofuel f during period t (units of product)
$\xi_{a,f}^{M}$	Max. production capacity of technology a for biofuel f (product output/year)
$\widetilde{\mu_f^m}$	Min. capacity used for the production technologies of biofuel type f
$\xi_{a,e}^{M}$	Max. production capacity of technology a for bioenergy e (MW/year)
$\widetilde{\mu_e^m}$	Minimum capacity used for production technologies of bioenergy type e
$\psi_{r,a}$	Equals 1, if technology a can convert biomass type r; 0, otherwise
φ	A number large enough
$\widetilde{\varsigma_{r,s,t}^{B}}$	The purchasing/producing/collecting cost of 1 unit biomass type r in supply source s during period t (\$/ton)
$\widetilde{\varsigma_{a,b,t}^{F}}$	Fixed cost of technology a at location b in period t (\$)
$\widetilde{\varsigma_{b,a,t}^{V}}$	Variable conversion costs of 1 unit biomass in location b by technology a in period t (\$/ton)
$\widetilde{\varsigma_{r,s,b,t}^{B,T}}$	Cost of transporting 1 unit type r biomass to location b from supply source s during period t (\$/ton)
$\widetilde{\varsigma_{f,b,c,t}^{B,T}}$	Cost of transporting 1 unit type f biofuel to market c from location b during period t (\$/unit product)
$\widetilde{\varsigma_{e,b,t}^{E}}$	Energy supply cost (1 unit type e bioenergy) of current sources at location b during period t (\$/MWh)
$\widetilde{\varsigma_{f,b}^{H}}$	Cost of holding 1 unit biofuel type f in bio-refinery b (\$/unit of product)
$\widetilde{\varpi_{f,t}^{T}}$	Total targeted demand for biofuel type f in any period t (units of product), e.g., could be imposed by government.
Decision variable	
$U_{r,s,b,t}$	Amount of biomass type r transported from supply source s to location b in period t (ton)
$U_{r,b,a,t}^{U}$	Amount of biomass type r used in technology a at location b during period t (ton)
$J_{e,b,t}^{C}$	Amount of energy (bioenergy type e) from available sources used in all technologies at location b during period t (MWh)
$P_{f,b,a,t}$	Amount of biofuel f produced at location b with technology a during period t (units of product)
$P_{f,b,c,t}^{M}$	Amount of biofuel f transported from location b to market c in period t (units of product)
$G_{e,b,a,t}$	Amount of bioenergy e produced at location b with technology a during period t (units of product)
$G_{e,b,t}^{S}$	Amount of bioenergy type e sold to external customers in location b during period t (MWh)
$G_{e,b,t}^{U}$	Amount of bioenergy type e used to meet the demand of all technologies at location b during period t (MWh)
$I_{f,b,t}^{B}$	Inventory of biofuel type f in bio-refinery b at the end of period t (units of product)
$Y_{b,a,t}$	Equals 1 if technology a is installed/launched at location b in period t, 0 otherwise
$M_{f,c}$	Equals 1 if area c is selected as the pilot market for biofuel f, 0 otherwise.

References

.1 Gilani, H. and H. Sahebi, *A multi-objective robust optimization model to design sustainable sugarcane-to-biofuel supply network: the case of study.* Biomass Conversion and Biorefinery, 2020: p. 1-22.

.2 d'Amore, F. and F. Bezzo, *Strategic optimisation of biomass-based energy supply chains for sustainable mobility.* Computers & Chemical Engineering, 2016. **87**: p. 68-81.

.3 Shavazipour, B., J. Stray, and T.J. Stewart, *Sustainable Planning in Sugar-Bioethanol Supply Chain under Deep Uncertainty: A case study of South African sugarcane industry.* Computers & Chemical Engineering, 2020: p. 107091.

.4 Razm, S., et al., *A global bioenergy supply network redesign through integrating transfer pricing under uncertain condition.* Journal of Cleaner Production, 2019. **2** :08 p. 1081-1095.

.5 Razm, S., S. Nickel, and H. Sahebi, *A multi-objective mathematical model to redesign of global sustainable bioenergy supply network.* Computers & Chemical Engineering, 2019. **128**: p. 1-20.

.6 Yue, D., F. You, and S.W. Snyder, *Biomass-to-bioenergy and biofuel supply chain optimization: overview, key issues and challenges.* Computers & Chemical Engineering, 2014. **66**: p. 36-56.

.7 Demirbas, M.F., M. Balat, and H. Balat, *Potential contribution of biomass to the sustainable energy development* .Energy Conversion and Management, 2009. **50**(7): p. 1746-1760.

.8 McKendry, P., *Energy production from biomass (part 1): overview of biomass.* Bioresource technology, 2002. **83**(1): p. 37-46.

.9 Campbell, K., *A feasibility study guide for an agricultural biomass pellet company.* Agricultural Utilization Research Institute, USA, 2007.

.10 McKendry, P., *Energy production from biomass (part 2): conversion technologies.* Bioresource technology, 2002. **83**(1): p. 47-54.

.11 You, F., et al., *Optimal design of sustainable cellulosic biofuel supply chains: multiobjective optimization coupled with life cycle assessment and input–output analysis.* AIChE Journal, 2012. **58**(4): p. 1157-1180.

.12 Awudu, I. and J. Zhang, *Stochastic production planning for a biofuel supply chain under demand and price uncertainties.* Applied Energy, 2013. **103**: p. 189-196.

.13 De Meyer, A., et al., *Methods to optimise the design and management of biomass-for-bioenergy supply chains: A review.* Renewable and sustainable energy reviews, 2014. **31**: p.657-670 .

.14 Demirbaş, A., *Biomass resource facilities and biomass conversion processing for fuels and chemicals.* Energy conversion and Management, 2001. **42**(11): p. 1357-1378.

.15 Union, E., *Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources and amending and subsequently repealing Directives 2001/77/EC and 2003/30/EC.* Official Journal of the European Union, 2009. **5**: p. 2009.

.16 Nguyen, D.H. and H. Chen, *Supplier selection and operation planning in biomass supply chains with supply uncertainty.* Computers & Chemical Engineering, 2018. **118**: p. 103-117.

.17 Arabani, A.B. and R.Z. Farahani, *Facility location dynamics: An overview of classifications and applications* .Computers & Industrial Engineering, 2012. **62**(1): p. 408-420.
.18 Soren, A. and Y. Shastri, *Resilient design of biomass to energy system considering uncertainty in biomass supply.* Computers & Chemical Engineering, 2019. **131**: p. 106593.
.19 Schmidt, J., et al., *Potential of biomass-fired combined heat and power plants considering the spatial distribution of biomass supply and heat demand.* International Journal of Energy Research, 2010. **34**(11): p. 970-985.
.20 Marvin, W.A., et al., *Economic optimization of a lignocellulosic biomass-to-ethanol supply chain.* Chemical Engineering Science, 2012. **67**(1): p. 68-79.
.21 Vikash, P.V. and Y. Shastri, *Conceptual design of a lignocellulosic biorefinery and its supply chain for ethanol production in India.* Computers & Chemical Engineering, 2019. **121**: p. 696-721.
.22 Bairamzadeh, S., M. Saidi-Mehrabad, and M.S. Pishvaee, *Modelling different types of uncertainty in biofuel supply network design and planning: A robust optimization approach.* Renewable energy, 2018. **116**: p. 5.00-517
.23 Santibañez-Aguilar, J.E., et al., *Sequential Use of Geographic Information System and Mathematical Programming for Optimal Planning for Energy Production Systems from Residual Biomass.* Industrial & Engineering Chemistry Research, 2019. **58** :(35) p. 15818-15837.
.24 Mohseni, S., M.S. Pishvaee, and H. Sahebi, *Robust design and planning of microalgae biomass-to-biodiesel supply chain: A case study in Iran.* Energy, 2016. **111**: p. 736-755.
.25 Rabbani, M., et al., *Developing a sustainable supply chain optimization model for switchgrass-based bioenergy production: A case study.* Journal of Cleaner Production, 2018. **200**: p. 827-843.
.26 Bairamzadeh, S., M.S. Pishvaee, and M. Saidi-Mehrabad, *Multiobjective robust possibilistic programming approach to sustainable bioethanol supply chain design under multiple uncertainties.* Industrial & Engineering Chemistry Research, 2015. **55**(1): p. 237-256.
.27 Ghaderi, H., M.S. Pishvaee, and A. Moini, *Biomass supply chain network design: an optimization-oriented review and analysis.* Industrial crops and products, 2016. **94**: p. 972-1000.
.28 Carter, C.R. and D.S. Rogers, *A framework of sustainable supply chain management: moving toward new theory.* International journal of physical distribution & logistics management, 2008 :(5)38 .p. 360-387.
.29 Bijarchiyan, M., H. Sahebi, and S. Mirzamohammadi, *A sustainable biomass network design model for bioenergy production by anaerobic digestion technology: using agricultural residues and livestock manure.* Energy, Sustainability and Society, 2020. **10**(1): p. 1-17.
.30 Dal-Mas, M., et al., *Strategic design and investment capacity planning of the ethanol supply chain under price uncertainty.* Biomass and bioenergy, 2011. **35**(5): p. 2059-2071.
.31 Kostin, A., et al., *Design and planning of infrastructures for bioethanol and sugar production under demand uncertainty.* Chemical Engineering Research and Design, 2012. **90**(3): p. 359-376.
.32 Chen, C.-W. and Y. Fan, *Bioethanol supply chain system planning under supply and demand uncertainties.* Transportation Research Part E: Logistics and Transportation Review, 2012. **48**(1): p. 150-164.

.33 Osmani, A. and J. Zhang, *Economic and environmental optimization of a large scale sustainable dual feedstock lignocellulosic-based bioethanol supply chain in a stochastic environment.* Applied energy, 2014. **114**: p. 572-587.
.34 Melo, M.T., S. Nickel, and F. Saldanha-Da-Gama, *Facility location and supply chain management–A review.* European journal of operational research, 2009. **196**(2): p. 401-412.
.35 Murillo-Alvarado, P.E., et al., *Multi-objective optimization of the supply chain of biofuels from residues of the tequila industry in Mexico.* Journal of Cleaner Production, 2015. **108**: p. 422-441.
.36 Ahmed, W. and B. Sarkar, *Impact of carbon emissions in a sustainable supply chain management for a second generation biofuel.* Journal of Cleaner Production, 2018. **186**: p. 807-820.
.37 Gonela, V., et al., *Stochastic optimization of sustainable hybrid generation bioethanol supply chains.* Transportation research part e: Logistics and transportation review, 2015. **77**: p. 1-28.
.38 Saghaei, M., H. Ghaderi, and H. Soleimani, *Design and optimization of biomass electricity supply chain with uncertainty in material quality, availability and market demand.* Energy, 2020. **197**: p. 1.17165
.39 Balaman, Ş.Y. and H. Selim, *A decision model for cost effective design of biomass based green energy supply chains.* Bioresource technology, 2015. **191**: p. 97-109.
.40 Osmani, A. and J. Zhang, *Stochastic optimization of a multi-feedstock lignocellulosic-based bioethanol supply chain under multiple uncertainties.* Energy, 2013. **59**: p. 157-172.
.41 Khishtandar, S., *Simulation based evolutionary algorithms for fuzzy chance-constrained biogas supply chain design.* Applied Energy, 2019. **236**: p. 183-195.
.42 Perpiña, C., J.C. Martínez-Llario, and Á. Pérez-Navarro, *Multicriteria assessment in GIS environments for siting biomass plants.* Land Use Policy, 2013. **31**: p. 326-335.
.43 Teixeira, T.R., et al., *Forest biomass power plant installation scenarios.* Biomass and Bioenergy, 2018. **108**: p. 35-47.
.44 Vukašinović, V. and D. Gordić, *Optimization and GIS-based combined approach for the determination of the most cost-effective investments in biomass sector.* Applied energy, 2016. **178**: p. 250-259.
.45 Zhang, F ,.et al., *Integrating GIS with optimization method for a biofuel feedstock supply chain.* Biomass and Bioenergy, 2017. **98**: p. 194-205.
.46 Wheeler, J., et al., *Combining multi-attribute decision-making methods with multi-objective optimization in the design of biomass supply chains.* Computers & Chemical Engineering, 2018. **113**: p. 11-31.
.47 Malczewski, J., *GIS-based land-use suitability analysis: a critical overview.* Progress in planning, 2004. **62**(1): p. 3-65.
.48 Rabbani, M., et al., *Optimal design for sustainable bioethanol supply chain considering the bioethanol production strategies: A case study.* Computers & Chemical Engineering, 2020. **134**: p. 106720.
.49 Zareei, S., *Evaluation of biogas potential from livestock manures and rural wastes using GIS in Iran.* Renewable Energy, 2018. **118**: p. 351-356.
.50 Zhang, F., D.M. Johnson, and J.W. Sutherland, *A GIS-based method for identifying the optimal location for a facility to convert forest biomass to biofuel.* biomass and bioenergy, 2011. **35**(9): p. 3951-3961.
.51 Sultana, A. and A. Kumar, *Optimal siting and size of bioenergy facilities using geographic information system.* Applied Energy, 2012. **94**: p. 192-201.

.52 Nas, B., et al., *Selection of MSW landfill site for Konya, Turkey using GIS and multi-criteria evaluation.* Environmental monitoring and assessment, 2010. **160**(1-4): p. 491.
.53 Dehghani, E., et al., *Resilient solar photovoltaic supply chain network design under business-as-usual and hazard uncertainties.* Computers & Chemical Engineering, 2018. **111**: p. 28.8-310
.54 Pishvaee, M.S., M. Rabbani, and S.A. Torabi, *A robust optimization approach to closed-loop supply chain network design under uncertainty.* Applied Mathematical Modelling, 2011. **35**(2): p. 637-649.
.55 Li, Z., R. Ding, and C.A. Floudas, *A comparative theoretical and computational study on robust counterpart optimization: I. Robust linear optimization and robust mixed integer linear optimization.* Industrial & engineering chemistry research, 2011. **50**(18): p. 10567-10603.
.56 Soyster, A.L., *Convex programming with set-inclusive constraints and applications to inexact linear programming.* Operations research, 1973. **21**(5): p. 1154-1157.
.57 Ben-Tal, A. and A. Nemirovski, *Robust solutions of linear programming problems contaminated with uncertain data.* Mathematical programming, 2000. **88**(3): p. 411-424.
.58 El Ghaoui, L., F. Oustry, and H. Lebret, *Robust solutions to uncertain semidefinite programs.* SIAM Journal on Optimization, 1998. **9**(1): p. 33-52.
.59 Bertsimas, D. and M. Sim, *The price of robustness* .Operations research, 2004. **52**(1): p. 35-53.
.60 Saaty, T.L., *What is the analytic hierarchy process?*, in *Mathematical models for decision support*. 1988, Springer. p. 109-121.
.61 Rogers, J. and J. Brammer, *Estimation of the production cost of fast pyrolysis bio-oil.* biomass and bioenergy, 2012. **36**: p. 208-217.
.62 Lehtikangas, P., *Quality properties of pelletised sawdust, logging residues and bark.* Biomass and bioenergy, 2001. **20**(5): p. 351-360.
.63 Yue, D. and F. You, *Stackelberg-game-based modeling and optimization for supply chain design and operations: A mixed integer bilevel programming framework.* Computers & Chemical Engineering, 2017. **102**: p. 81-95.
.64 Tong, K., et al., *Stochastic programming approach to optimal design and operations of integrated hydrocarbon biofuel and petroleum supply chains.* ACS Sustainable Chemistry & Engineering, 2014. **2**(1): p. 49-61.
.65 Heat, B.C., *Power Catalog of Technologies.* US Environmental Protection Agency, Combined Heat and Power Partnership, 2007.
.66 Gorsevski, P.V., et al., *Integrating multi-criteria evaluation techniques with geographic information systems for landfill site selection: a case study using ordered weighted average.* Waste management, 2012. **32**(2): p. 287-296.
.67 Thornley, P., J. Rogers, and Y. Huang, *Quantification of employment from biomass power plants.* Renewable Energy, 2008. **33**(8): p. 1922-1927.
.68 Sultana, A., A. Kumar, and D. Harfield, *Development of agri-pellet production cost and optimum size.* Bioresource Technology, 2010. **101**(14): p. 5609.5621-
.69 Ghelichi, Z., J. Tajik, and M.S. Pishvaee, *A novel robust optimization approach for an integrated municipal water distribution system design under uncertainty: A case study of Mashhad.* Computers & Chemical Engineering, 2018. **110**: p. 13-34.