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A mathematical model for microalgae-based biobutanol supply chain network design under harvesting and drying uncertainties

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ABSTRACT

Microalgae is one of the most promising feedstocks for biofuel production because it yields the high content of sugar and oil. In order to help to develop this nascent industry, this paper proposes a mixed integer linear programming (MILP) model for planning and designing a microalgae-based biobutanol supply chain network. The goal of this study is minimizing the fixed cost of constructing required facilities, transportation costs, and operational costs (harvesting, pretreatment, treatment, and energy conversion). This paper considers supply, production, distribution, and addresses a multi-period model. Since the volume of harvested and dried algae cannot be determined accurately, a fuzzy programming approach is employed to address uncertainties. Additionally, a data envelopment analysis (DEA) method is used to reduce the complexity of solving the proposed model. The applicability of the model is evaluated through a real case study of Iran.

1. Introduction

Demand for energy has been increased due to the rapid growth of the world's population and the rise of developing countries [1]. Greenhouse gas (GHG) emissions, environmental pollution, and climate change are affiliated with the consumption of fossil fuels [2]. Due to reducing GHG emissions, the production of renewable biofuels from biomass has taken more interest [3]. Among the liquid biofuels, biobutanol is promising significantly by virtue of its excellent chemical and physical attributes. Biobutanol is known as the only “drop-in" biofuel which can be easily mixed with gasoline at a content of up to 85% [4]. Butanol can substitute ethanol as an additive to gasoline because of its benefits (see Table 1), such as high energy concentration and hybrid options in addition to its low vapor pressure. The physical attributes of butanol are those that modern gasoline engines can utilize butanol without any particular changes [5]. Besides, butanol is better for older vehicles because ethanol can ruin rubber seals, as opposed to butanol [6].

The widespread availability of algae has made it the promising feedstock for the third-generation [7]. Microalgae has a varied collection of prokaryotic and eukaryotic photosynthetic microorganisms which grows fast owing to its uncomplicated structure [8]. In addition, it is able to live in not only aquatic but also terrestrial environmental conditions. Broadly speaking, it is present in all earth ecosystems and microalgae has more than 50,000 species nevertheless, 30,000 have been investigated [9]. Algae is a feedstock for the production of biofuels due to the rapid growth rate, the high content of sugar and oil, and it has the ability to grow in the marginal waters of the earth. Most of the algal biofuel researches have focused on the usage of natural oils in algae for biodiesel production. However, most of the energy in algae is not stored as oil but stored as carbohydrates [10].

Although considerable researches have been done on the conversion of algae oils to biodiesel nevertheless, there are little researches on the conversion of starches and sugars to liquid fuels [6]. Carbohydrate-based microalgae can produce biobutanol, as an alternative fuel [11].

Uncertainty affects the performance of a supply chain and should be involved in several decision makings. Some uncertainties in a biofuel supply chain include biomass supply uncertainties, logistics and transportation uncertainties, price and demand uncertainties, and operation and production uncertainties. Integrating uncertainties in a supply chain include some methodologies: Analytical methods and Simulation methods [12]. Fuzzy programming approach is an efficient way to deal with uncertainties. Necessity concept is used in this paper according to the formula presented in Ref. [13].

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Table 1
Specifications of butanol in comparison with ethanol [45].

Characteristic	Ethanol	Butanol
Formula	C_2H_5OH	C_4H_9OH
Boiling point (°C)	78	118
Energy density (MJ Kg^{-1})	26.9	33.1
Air fuel ratio	9	11.2
Research octane number	129	96
Motor octane number	102	78
Heat of vaporization (MJ Kg^{-1})	0.92	0.43
Viscosity (10^{-3} Pa s)	1.078	2.593
Vapor pressure (kPa at 20 °C)	5.82,625	0.58

Considering the aforementioned points and depletion of the world fossil energy resources, it can be concluded that the micro-algal biofuel supply chain is increasingly getting more attention. A considerable amount of studies have been done in order to develop biofuel supply chain network design [14], but none has investigated a supply chain of biobutanol from algae. Some of these articles will be reviewed briefly in the following paragraphs.

For example in the bioethanol supply chain, Chen and Fan [15] have proposed a mixed integer stochastic programming model to support strategic planning of a bioethanol supply chain system and allocation of optimal feedstock resource in uncertain conditions. Akgul et al. [16] have developed a static multi-objective model to optimize the supply chains of a hybrid first/second generation bioethanol which concerns the land use necessities. Besides, they considered the effects of the carbon tax on fuel supply chain performance. Ho et al. [17] have investigated the potential of a carbohydrate-rich microalgae Chlorella Vulgaris FSP-E as a raw material for bioethanol production through various hydrolysis and fermentation procedures but they had qualitative design approach in their paper. Osmani and Zhang [18] have suggested a multi-objective optimization model for designing a sustainable multi-period second generation biomass-to-bioethanol supply chain under multiple uncertainties. Switchgrass, crop residue, and woody materials are the utilized feedstocks for mentioned supply chain in their work. Also, in biodiesel production Kim et al. [19] have addressed a model for optimal design of the biomass supply chain in uncertain conditions. They have discovered the design of a biofuel network in the United States from the perspective of fast pyrolysis and Fischer Tropsch biodiesel conversion processes by considering scenarios to work with uncertainties. Gong and You [20] have presented a consequential life cycle optimization (LCO) framework which optimizes the process design of algae-based biodiesel. Besides, it determines the environmental effects and economic performance, simultaneously. They showed that the net present value (NPV) was impressed by biodiesel price significantly and the environmental effect was susceptible to fertilizers price. Nodooshan et al. [21] have addressed a multi-objective algal biofuel supply chain model which considers the main features of algal biofuel supply chain network for a sustainable production of biodiesel. Their model minimizes the total life cycle GHG emission and total cost of the supply chain. An integrated green biodiesel supply chain network has designed by Ghelichi et al. [22]. They have proposed a two-stage stochastic programming model and considered Jatropha Curcas as the feedstock. The proposed model is mixed-integer linear programming, multi-period, and multi-product. Also, they have implemented their model in a real case study of Iran to evaluate the performance of it.

Some researchers have employed Geographic Information System (GIS) technology to design the biofuel supply chain networks. For instance, the ArcGIS platform is utilized to identify longitudes and latitudes of harvesting areas, storage yards and biorefinery candidates for an integrated multi-stage, mixed integer programming model [23]. Another research has implemented GIS to locate biofuel facilities by considering a series of decision factors with simulation and optimization for a biofuel supply chain [24]. Also, Zhang et al. [25] have integrated GIS with an optimization method for a biofuel supply chain network. In their research, candidate bioethanol facilities as inputs for the optimization model have preselected using GIS method.

There are many studies which have worked on the biofuel supply chain network design. some of them have studied the supply chains with multiple feedstocks, biofuels or periods. In contrast, some are single in feedstock, biofuel or period. There are three aspects of the supply chain in the studies: supply, production, and distribution. Besides, few articles are precisely defined in production steps. On the other hand, some have described the steps generally. The review of these articles is in the following paragraphs.

Ekşioğlu et al. [26] have proposed a mathematical model to determine the size, number, and location of the biorefineries needed to produce biofuels from available biomass. Also, their proposed model decides the amount of biomass transported, processed, and stored during a period. They realized that it is better to construct two or three tiny size plants instead of constructing a big one, for small conversion rates. Van Dyken et al. [27] have presented a linear mixed-integer model for fundamental ingredients in a biomass supply chain containing supply, treating, storing, and different types of biomass demand. Huang et al. [28] have provided a mathematical model aimed at minimizing the cost of the entire supply chain of biofuels from bio-waste feedstock to final consumers throughout the planning horizon while considering demand satisfaction, resources, and the constraint of technology. Actually, they integrated the knowledge of renewable energy technologies into operational research to develop future energy sustainability. Papapostolou et al. [29] have expanded a mathematical model for designing and operating a supply chain of biofuel which considers the economic and technical parameters which have an effect on the performance of the value chain. Kim et al. [30] have developed an MILP model that enables the selection of biofuel transformation processing infrastructure, biomass locations, capacities, and transportation logistics. They have used the optimization model to design an optimal network for maximizing profits by considering the purchasing cost of biomass, investment cost, operating cost, transportation cost, and sales prices for different potential markets. Zhang et al. [31] have proposed a simulation-based model for biofuel supply chain. The model pays attention to key supply chain activities which consist of biomass collection/processing, transportation, and storing activities. Also, they discussed land use competition and uncertainty management in the biofuel supply chain. Ubando et al. [32] have presented a multi-objective fuzzy linear programming model to design an algal biofuel polygeneration supply chain with a single region. Furthermore, they considered triple footprints such as water, land, and carbon. Then, Ubando et al. [33] have addressed a multi-objective fuzzy linear programming model to design an algal biofuel polygeneration supply chain among several regions. The objectives include product demand satisfaction, environmental footprint minimization, and economic performance maximization. Besides, they compared two kinds of cultivation systems considering the mentioned goals and concluded that flat-plate photobioreactor is better than raceway pond. Ubando et al. [34] have designed a multi-functional bioenergy system by proposing a fuzzy mixed-integer linear programming. The mentioned system considered economic performance, carbon footprint, and the demand for multiple products through the integration of producing biochar. It was realized from the consequences that net negative carbon footprint could be gained from suchlike systems. Yue et al. [35] have presented a multi-period, multi-product, multi-scale mixed integer nonlinear programming model which minimizes the CO_2 emissions and costs at the same time. The model considers the network design of CO_2 gas transportation pipeline, the processing route of microalgae, and the analysis of CO_2 resources seasonal accessibility. They showed that biofuels production cause to development of GHG reduction effect and reduced cost of CO_2 diminution. Ubando et al. [36] have developed a fuzzy mixed integer non-linear programming for designing an algae-based eco-industrial park. The proposed model maximizes the annual profit of each company in the eco-industrial park and satisfies the product demand. Besides, it minimizes the environmental footprint of the eco-industrial park. Ubando et al. [37] have evaluated alternative algae cultivation systems using a multi-criteria method based on analytic hierarchy process (AHP). Besides, uncertainty scenarios were analyzed by Monte Carlo simulation, and the results indicated which cultivation system is preferred for optimistic (risk-inclined) and conservative (risk-averse) scenarios. Sy et al. [38] have presented a multi-objective model oriented robust optimization in order to deal with uncertainties in fluctuations in product demand or seasonal changes when acquiring an integrated biorefinery design. Environmental and profit footprints were considered via model during optimization and multiple scenarios were considered by Monte Carlo simulation.

There are several methods for reducing the complexity of the model. We have investigated some of them and finally, the DEA approach is chosen by virtue of its advantages over other methods. Charnes and Cooper [39] presented DEA approach as a non-parametric method in such situations to measure the efficiency of decision-making units (DMUs). Some of the advantages of DEA approach over other methods are described as follows:

- ✓ By comparing the DEA approach with stochastic frontier analysis (SFA) it is found out that DEA necessitates marginal assumptions and it is non-parametric. In contrast, SFA involves strong assumptions and it is parametric [40].
- ✓ One of the basic advantages of DEA is weight flexibility [41].
- ✓ By comparing the DEA approach with multi-criteria decision making (MCDM) it is understood that DEA without relying on the usage of input and output weights, supplies an efficiency measure. On the other hand, the MCDM approach is based on the supposition that a set of weights should be used in all units [42]. Broadly speaking, it can be mentioned that human factors are not involved in DEA method but decision-maker opinion is involved in MCDM approach.
- ✓ DEA approach has multiple advantages over other parametric methods in relation to appraising the relative efficiency of R&D operations. First, DEA can overcome the problem of non-defined produced inputs and outputs due to the absence of market prices. Second, DEA presumes that at least one DMU is technically effective to define the efficiency boundary [43].

Generally speaking, algal biofuel supply chain includes harvesting, drying, hydrolyzing, and biorefinery plant operations [6]. In a review by Yue et al. [44] majority of the researches are worked on supply chain design, but there are a few studies in which the planning and operation of biorefineries have been integrated into the supply chain models. According to the relevant literature, there are few papers which considered production steps precisely. Also, there is no study to consider algae-based biobutanol supply chain network design. For more details please refer to Table 2.

This paper proposes an MILP model that minimizes the entire costs of microalgae-based biobutanol supply chain. The main

Table 2
Literature review of biofuel production.

References	Design Approach		Production Steps				Feedstock Generation					Product				Using DEA	Aspect of Supply Chain		
	Qualitative	Quantitative	Harvesting	Pretreatment	Treatment	Energy Conversion	First Generation	Second Generation	Third Generation: Microalgae	Third Generation: Macroalgae	Not Specified	Biobutanol	Bioethanol	Biodiesel	Not Specified		Supply	Production	Distribution
[26]		*	*			*		*					*				*	*	*
[19]		*	*		*	*					*			*			*	*	*
[30]		*	*		*	*					*			*			*	*	*
[46]	*		*	*	*	*				*		*					*	*	
[6]	*				*	*				*		*					*	*	
[15]		*		*		*					*		*				*	*	*
[31]		*	*			*					*				*		*	*	
[16]		*		*		*	*	*					*				*	*	*
[17]	*				*	*			*			*					*	*	
[33]		*				*			*					*			*	*	*
[18]		*	*			*		*					*				*	*	*
[20]		*	*	*	*	*			*					*			*	*	*
[21]		*	*	*	*	*			*					*			*	*	*
This Article		*	*	*	*	*			*			*				*	*	*	*

contributions of this paper which differentiate it from other efforts in this field are as follows:

- Developing a mathematical model into a specialized supply chain network design of biobutanol from microalgae
- Considering all aspects of supply chain including supply, production, and distribution
- Employing a fuzzy programming approach in order to address uncertainties
- Using a DEA method to reduce the complexity of solving the proposed model

The rest of the paper is organized as follows: in section 2, the microalgae-based biobutanol supply chain is described. The mathematical model is presented in section 3. The fuzzy model is explained in section 4. The proposed model is implemented in a real case study in Iran in section 5. Finally, Section 6 demonstrates the conclusion of this paper.

2. Problem statement

According to the literature review, in this research, a supply chain network design of producing biobutanol from microalgae is developed. This supply chain begins with the algae harvesting which includes two stages of thickening and dewatering. It is noteworthy to mention that harvesting can be done by some methods such as mechanical, chemical and biological. In the next step, the harvested algae is dried by using drying facilities. There are some technologies for dewatering such as filtration, flotation thickening, and concentration. Flotation thickening is not strong in dewatering effects but it is an inexpensive technology. Filtration and concentration technologies are the expensive technologies which have the ability to dry the solid content significantly [47,48]. Next phase is the hydrolyzing step, in which starches of the algae is converted to fermentable sugars [46]. This stage is commonly done by strong acids or enzymes [44]. Next step is acetone butanol ethanol (ABE) fermentation in biobutanol refinery. In this fermentation, materials pass pyruvate workstation, acetyl coa workstation, acetoacetyl coa workstation, and butyryl coa workstation, respectively. ABE fermentation is typically limited to Clostridium species [49]. Anaerobic bacteria in the genus Clostridium transform simple sugar to acetone, butanol, and ethanol in a 3: 6: 1 vol ratio, respectively in ABE fermentation system. Finally, the produced biobutanol is transported from biobutanol refinery plants to customers (Fig. 1). Focusing on producing butanol, the other products of the ABE fermentation are neglected due to the fixed price of them that cannot affect the objective function of this research. Different kinds of transportation modes can be utilized in the mentioned supply chain such as rail and road transportations.

3. Deterministic model

Considering the aforementioned points, a mathematical model is proposed without taking any uncertainty into account. The model considers three important aspects of supply chain including supply (harvesting), production (pretreatment, treatment, and energy conversion), and distribution. The model determines the best locations for harvesting, drying, hydrolyzing, and biobutanol refinery plant. Also, it decides about constructing the workstations and the amount of transported material between locations and workstations. There is inventory in drying locations, hydrolyzing locations, and workstations that the proposed model determines the level of it.

3.1. Model formulation

Before describing the mathematical model the indices, the parameters, and the decision variables are defined below (see Tables 3–5).

3.1.1. Objective function

The purpose of this study is minimizing the total cost of biobutanol production which includes fixed and operational costs shown by TC_f and TC_O respectively.)

$$Min\ Z = TC_f + TC_o \tag{1}$$

TC_f Indicates the total fixed costs of constructing harvesting locations ($\sum_{i=1}^{I} fch_i YH_i$), drying locations ($\sum_{j=1}^{J} fcd_j YD_j$), hydrolyzing

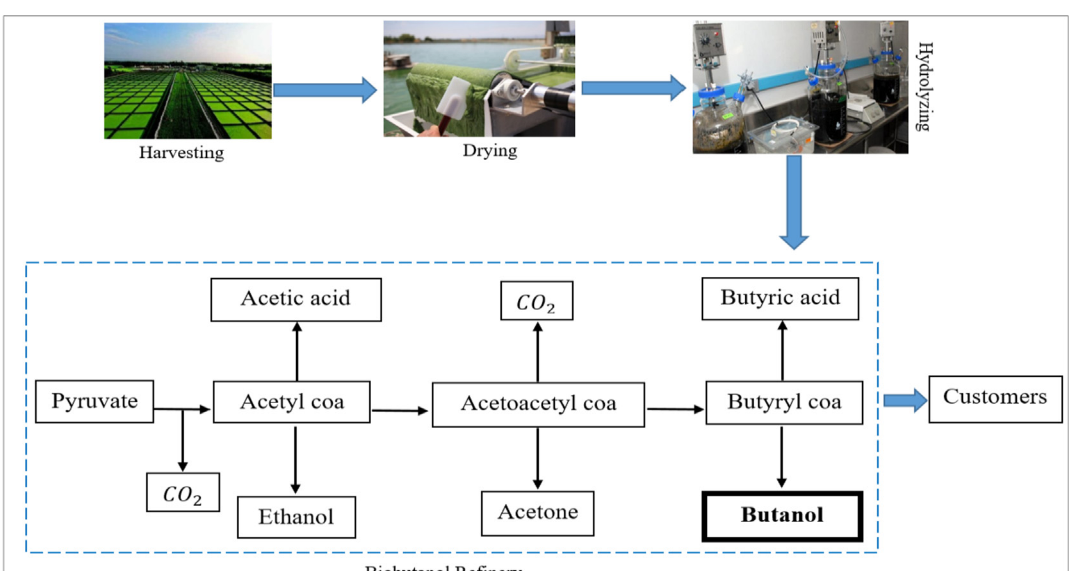

Fig. 1. Microalgae-based biobutanol supply chain.

locations ($\sum_{k=1}^{K} fcz_k YZ_k$), biobutanol refinery plants ($\sum_{h=1}^{H} fc_h Y_h$), pyruvate workstations ($\sum_{l=1}^{L}\sum_{h=1}^{H} fcp_{lh} YP_{lh}$), acetyl coa workstations ($\sum_{m=1}^{M}\sum_{h=1}^{H} fca_{mh} YA_{mh}$), acetoacetyl coa workstations ($\sum_{n=1}^{N}\sum_{h=1}^{H} fcac_{nh} YAC_{nh}$), and butyryl coa workstations ($\sum_{P=1}^{p}\sum_{h=1}^{H} fcb_{ph} YB_{ph}$).

$$TC_f = \sum_{i=1}^{I} fch_i YH_i + \sum_{j=1}^{J} fcd_j YD_j + \sum_{k=1}^{K} fcz_k YZ_k + \sum_{h=1}^{H} fc_h Y_h + \sum_{l=1}^{L} \times \sum_{h=1}^{H} fcp_{lh} YP_{lh} + \sum_{m=1}^{M}\sum_{h=1}^{H} fca_{mh} YA_{mh} + \sum_{n=1}^{N}\sum_{h=1}^{H} fcac_{nh} YAC_{nh} + \sum_{P=1}^{p}\sum_{h=1}^{H} fcb_{ph} YB_{ph} \tag{2}$$

TC_o Shows the total value of variable costs. It is calculated by summing operational costs of harvesting locations, drying locations, hydrolyzing locations, pyruvate workstations, acetyl coa workstations, acetoacetyl coa workstations, and butyryl coa workstations plus their transportation costs and the costs of bringing biobutanol to customers.

$$\begin{aligned} TC_o = & \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R}\sum_{t=1}^{T} och_i TRH_{ijrt} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{r=1}^{R}\sum_{t=1}^{T} ocd_j TRD_{jkrt} \\ & + \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R}\sum_{t=1}^{T} trch_{ijr} TRH_{ijrt} + \sum_{j=1}^{J}\sum_{k=1}^{K}\sum_{r=1}^{R}\sum_{t=1}^{T} trcd_{jkr} TRD_{jkrt} \\ & + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{h=1}^{H}\sum_{r=1}^{R}\sum_{t=1}^{T} ocz_k TRZ_{klhrt} + \sum_{k=1}^{K}\sum_{l=1}^{L}\sum_{h=1}^{H}\sum_{r=1}^{R}\sum_{t=1}^{T} trcz_{khr} TRZ_{klhrt} \\ & + \sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{h=1}^{H} ocp_l TRP_{lmth} + \sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{h=1}^{H} trcp_{lm} TRP_{lmth} \\ & + \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{h=1}^{H} oca_m TRA_{mnth} + \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{h=1}^{H} trca_{mn} TRA_{mnth} \\ & + \sum_{n=1}^{N}\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{h=1}^{H} ocac_n TRAC_{npth} + \sum_{n=1}^{N}\sum_{p=1}^{P}\sum_{t=1}^{T}\sum_{h=1}^{H} trcac_{np} TRAC_{npth} \\ & + \sum_{p=1}^{P}\sum_{e=1}^{E}\sum_{h=1}^{H}\sum_{r=1}^{R}\sum_{t=1}^{T} ocb_p TRB_{phert} + \sum_{p=1}^{P}\sum_{e=1}^{E}\sum_{h=1}^{H}\sum_{r=1}^{R}\sum_{t=1}^{T} trc_{her} TRB_{phert} \end{aligned}$$

3.1.2. Constraints

Eq. (4) ensures that the dry algae inventory level at the end of period$t$ in every drying location j ($INVD_{jt}$) is equal to γ fold of the all transported harvested algae from harvesting locations ($\gamma \sum_{i=1}^{I}\sum_{r=1}^{R} TRH_{ijrt}$) that γ has defined in some percentages which have discussed in Ref. [50], subtracting transported dry algae to all hydrolyzing locations ($\sum_{k=1}^{K}\sum_{r=1}^{R} TRD_{jkrt}$) plus the dry algae inventory level at the end of period $t-1$ ($INVD_{j,t-1}$).

Table 3
Indices.

i	Suggested locations for harvesting algae($i = 1....I$))
j	Suggested locations for drying algae ($j = 1.....J$)
k	Suggested locations for hydrolyzing algae ($k = 1.....K$)
l	Pyruvate workstations ($l = 1.....L$)
m	Acetyl coa workstations($m = 1.....M$)
n	Acetoacetyl coa workstations ($n = 1.....N$)
p	Butyryl coa workstations ($p = 1.....P$)
r	Transportation modes($r = 1.....R$)
t	Periods($t = 1.....T$)
h	Suggested locations for biobutanol refinery plant($h = 1.....H$)
e	Customers($e = 1.....E$)

$$INVD_{jt} = \gamma \sum_{i=1}^{I}\sum_{r=1}^{R} TRH_{ijrt} - \sum_{k=1}^{K}\sum_{r=1}^{R} TRD_{jkrt} + INVD_{j,t-1} \ \forall j,\ t \tag{4}$$

Eq. (5) ensures that the glucose inventory level in every hydrolyzing location k at the end of period$t$ ($INVZ_{kt}$) is equal to ψ fold of the all transported dry algae from drying locations ($\psi \sum_{j=1}^{J}\sum_{r=1}^{R} TRD_{jkrt}$) which ψ has defined in some percentages that [51] have discussed about it, Subtracting transported glucose to all pyruvate workstations in biobutanol refineries ($\sum_{l=1}^{L}\sum_{r=1}^{R} TRZ_{klhrt}$) plus the glucose inventory level at the end of period$t-1$ ($INVZ_{k,t-1}$).

$$INVZ_{kt} = \psi \sum_{j=1}^{J}\sum_{r=1}^{R} TRD_{jkrt} - \sum_{l=1}^{L}\sum_{r=1}^{R} TRZ_{klhrt} + INVZ_{k,t-1} \ \forall k,\ t \tag{5}$$

Eq. (6) ensures that the material inventory level at the end of period$t$ in every pyruvate workstation l in every biobutanol refinery plant h ($INVP_{lth}$) is equal to φ fold of the all transported glucose from hydrolyzing locations ($\varphi \sum_{k=1}^{K}\sum_{r=1}^{R} TRZ_{klhrt}$) that has defined in some percentages as defined in Ref. [6], subtracting transported material to acetyl coa workstation ($\sum_{m=1}^{M} TRP_{lmth}$) plus the material inventory level at the end of period$t-1$ ($INVP_{l,t-1,h}$).

$$INVP_{lth} = \varphi \sum_{k=1}^{K}\sum_{r=1}^{R} TRZ_{klhrt} - \sum_{m=1}^{M} TRP_{lmth} + INVP_{l,t-1,h} \ \forall l, t, h \tag{6}$$

Eq. (7) ensures that the material inventory level at the end of period$t$ in every acetyl coa workstation m in every biobutanol refinery plant h ($INVA_{mth}$) is equal to τ fold of the all transported material from pyruvate workstation ($\tau \sum_{l=1}^{L} TRP_{lmth}$) as defined in some percentages in Ref. [6], subtracting transported material to acetoacetyl coa workstation ($\sum_{n=1}^{N} TRA_{mnth}$) plus the material inventory level at the end of period$t-1$ ($INVA_{m,t-1,h}$).

$$INVA_{mth} = \tau \sum_{l=1}^{L} TRP_{lmth} - \sum_{n=1}^{N} TRA_{mnth} + INVA_{m,t-1,h} \ \forall m,\ t, h \tag{7}$$

Eq. (8) ensures that the material inventory level at the end of

Table 4
Parameters.

fch_i	Fixed cost of constructing the suggested harvesting location i for algae
fcd_j	Fixed cost of constructing the suggested drying location j for algae
fcz_k	Fixed cost of constructing the suggested hydrolyzing location k for algae
fc_h	Fixed cost of constructing suggested biobutanol refinery plant h
fcp_{lh}	Fixed cost of constructing suggested workstation l in suggested biobutanol refinery plant h
fca_{mh}	Fixed cost of constructing suggested workstation m in suggested biobutanol refinery plant h
$fcac_{nh}$	Fixed cost of constructing suggested workstation n in suggested biobutanol refinery plant h
fcb_{ph}	Fixed cost of constructing suggested workstation p in suggested biobutanol refinery plant h
och_i	Operational cost of harvesting in suggested location i for per unit of algae
ocd_j	Operational cost of drying in suggested location j for per unit of algae
ocz_k	Operational cost of hydrolyzing in suggested location k for per unit of algae
ocp_l	Operational cost of workstation l for processing per unit of material
oca_m	Operational cost of workstation m for processing per unit of material
$ocac_n$	Operational cost of workstation n for processing per unit of material
ocb_p	Operational cost of workstation p for processing per unit of material
$trch_{ijr}$	Transportation cost from suggested location i to j under transport mode r for per unit of algae
$trcd_{jkr}$	Transportation cost from suggested location j to k under transport mode $r$for per unit of algae
$trcz_{khr}$	Transportation cost from suggested location k to h under transport mode r for per unit of material
$trcp_{lm}$	Transportation cost from location l to m for per unit of material
$trca_{mn}$	Transportation cost from location m to n for per unit of material
$trcac_{np}$	Transportation cost from location n to p for per unit of material
trc_{her}	Transportation cost from location h to customer e under transport mode r for per unit of butanol
$caph_i$	Capacity of suggested location i for harvesting algae
$capd_j$	Capacity of suggested location j for drying algae
$capz_k$	Capacity of suggested location k for hydrolyzing algae
$capp_l$	Processing capacity of pyruvate workstation l
$capa_m$	Processing capacity of acetyl coa workstation m
$capac_n$	Processing capacity of acetoacetyl coa workstation n
$capb_p$	Processing capacity of butyryl coa workstation p
d_{et}	Demand of customer e in period t
γ	Production factor of harvesting step
ψ	Production factor of drying step
φ	Production factor of hydrolyzing step
τ	Production factor of pyruvate workstation
α	Production factor of acetyl coa workstation
δ	Production factor of acetoacetyl coa workstation

Table 5
Decision variables.

YH_i	Binary variable indicates whether a harvesting location is constructed at suggested location i or not
YD_j	Binary variable indicates whether a drying location is constructed at suggested location j or not
YZ_k	Binary variable indicates whether a hydrolyzing location is constructed at suggested location k or not
Y_h	Binary variable indicates whether a biobutanol refinery plant is constructed at suggested location h or not
YP_{lh}	Binary variable indicates whether the pyruvate workstation l is constructed in biobutanol refinery plant h or not
YA_{mh}	Binary variable indicates whether the acetyl coa workstation m is constructed in biobutanol refinery plant h or not
YAC_{nh}	Binary variable indicates whether the acetoacetyl coa workstation n is constructed in biobutanol refinery plant h or not
YB_{ph}	Binary variable indicates whether the butyryl coa workstation p is constructed in biobutanol refinery plant h or not
TRH_{ijrt}	Amount of algae transported from suggested location $i$to $j$under transport mode r in period t
TRD_{jkrt}	Amount of algae transported from suggested location j to k under transport mode r in period t
TRZ_{klhrt}	Amount of transported material from suggested location k to pyruvate workstation l in biobutanol refinery plant h under transport mode r in period t
TRP_{lmth}	Amount of transported material from workstation l to m in period t in biobutanol refinery plant h
TRA_{mnth}	Amount of transported material from workstation m to n in period t in biobutanol refinery plant h
$TRAC_{npth}$	Amount of transported material from workstation n to p with in period t in biobutanol refinery plant h
TRB_{phert}	Amount of transported biobutanol from workstation p in biobutanol refinery plant h to customer e under transport mode r in period t
$INVD_{jt}$	Dried algae inventory in suggested location j in period t
$INVZ_{kt}$	Glucose inventory in suggested location k in period t
$INVP_{lth}$	Inventory level in suggested workstation l in period t in biobutanol refinery plant h
$INVA_{mth}$	Inventory level in suggested workstation m in period t in biobutanol refinery plant h
$INVAC_{nth}$	Inventory level in suggested workstation n in period t in biobutanol refinery plant h
$INVB_{pth}$	Inventory level in suggested workstation p in period t in biobutanol refinery plant h

period$t$ in every acetoacetyl coa workstation n in every biobutanol refinery plant h ($INVAC_{nth}$) is equal to α fold of the all transported material from acetyl coa workstation ($\alpha \sum_{m=1}^{M} TRA_{mnth}$) as defined in some percentages in Ref. [6], subtracting transported material to butyryl coa workstation ($\sum_{p=1}^{P} TRAC_{npth}$) plus the material inventory level at the end of period$t-1$ ($INVAC_{n,t-1,h}$).

$$INVAC_{nth} = \alpha \sum_{m=1}^{M} TRA_{mnth} - \sum_{p=1}^{P} TRAC_{npth} + INVAC_{n,t-1,h} \ \forall n,\ t, h \tag{8}$$

Eq. (9) ensures that the biobutanol inventory level at the end of period$t$ in every butyryl coa workstation p in every biobutanol refinery plant$h$ ($INVB_{pth}$) is equal to δ fold of the all transported material from acetoacetyl coa workstation ($\delta \sum_{n=1}^{N} TRAC_{npth}$) as defined in some percentages in Ref. [6], subtracting transported biobutanol to all customers ($\sum_{e=1}^{E} \sum_{r=1}^{R} TRB_{phert}$) plus the biobutanol inventory level at the end of period$t-1$ ($INVB_{p,t-1,h}$).

$$INVB_{pth} = \delta \sum_{n=1}^{N} TRAC_{npth} - \sum_{e=1}^{E} \sum_{r=1}^{R} TRB_{phert} + INVB_{p,t-1,h} \ \forall p,\ t, h \tag{9}$$

Eq. (10) ensures that in every harvesting location i and period$t$, transported harvested algae to all drying locations ($\sum_{j=1}^{J} \sum_{r=1}^{R} TRH_{ijrt}$) does not exceed the capacity of harvesting location i ($caph_i YH_i$)if it is constructed.

$$\sum_{j=1}^{J} \sum_{r=1}^{R} TRH_{ijrt} \leq caph_i YH_i \ \forall i,\ t \tag{10}$$

Eq. (11) ensures that in every drying location j and period t, transported dry algae to all hydrolyzing locations ($\sum_{k=1}^{K} \sum_{r=1}^{R} TRD_{jkrt}$) does not exceed the capacity of drying location j ($capd_j YD_j$) if it is constructed, plus the algae inventory level at the end of period$t-1$ ($INVD_{j,t-1}$).

$$\sum_{k=1}^{K} \sum_{r=1}^{R} TRD_{jkrt} \leq capd_j YD_j + INVD_{j,t-1} \ \forall j,\ t \tag{11}$$

Eq. (12) ensures that in every hydrolyzing location k and period$t$, transported glucose to all pyruvate workstations in biobutanol refineries ($\sum_{h=1}^{H} \sum_{r=1}^{R} \sum_{l=1}^{L} TRZ_{klhrt}$) does not exceed the capacity of hydrolyzing location k ($capz_k YZ_k$) if it is constructed, plus the glucose inventory level at the end of period$t-1$ ($INVZ_{k,t-1}$).

$$\sum_{h=1}^{H} \sum_{r=1}^{R} \sum_{l=1}^{L} TRZ_{klhrt} \leq capz_k YZ_k + INVZ_{k,t-1} \ \forall k,\ t \tag{12}$$

Eq. (13) ensures that in every pyruvate workstation l and biobutanol refinery h in period$t$, transported material to acetyl coa workstation ($\sum_{m=1}^{M} TRP_{lmth}$) does not exceed the capacity of pyruvate workstation l ($capp_l YP_{lh}$) if it is constructed, plus the material inventory level at the end of period$t-1$ ($INVP_{l,t-1,h}$).

$$\sum_{m=1}^{M} TRP_{lmth} \leq capp_l YP_{lh} + INVP_{l,t-1,h} \ \forall l,\ t,\ h \tag{13}$$

Eq. (14) ensures that in every acetyl coa workstation m and biobutanol refinery h in period$t$, transported material to acetoacetyl coa workstation ($\sum_{n=1}^{N} TRA_{mnth}$) does not exceed the capacity of acetyl coa workstation m ($capa_m YA_{mh}$) if it is constructed, plus the material inventory level at the end of period$t-1$ ($INVA_{m,t-1,h}$).

$$\sum_{n=1}^{N} TRA_{mnth} \leq capa_m YA_{mh} + INVA_{m,t-1,h} \ \forall m,\ t,\ h \tag{14}$$

Eq. (15) ensures that in every acetoacetyl coa workstation n and biobutanol refinery h in period$t$, transported material to butyryl coa workstation ($\sum_{p=1}^{P} TRAC_{npth}$) does not exceed the capacity of acetoacetyl coa workstation n ($capac_n YAC_{nh}$) if it is constructed, plus the material inventory level at the end of period$t-1$ ($INVAC_{n,t-1,h}$).

$$\sum_{p=1}^{P} TRAC_{npth} \leq capac_n YAC_{nh} + INVAC_{n,t-1,h} \ \forall n, t, h \tag{15}$$

Eq. (16) ensures that in every butyryl coa workstation p and biobutanol refinery plant h in period$t$, transported biobutanol to all customers ($\sum_{e=1}^{E} \sum_{r=1}^{R} TRB_{phert}$) does not exceed the capacity of butyryl coa workstation$p$ ($capb_p YB_{ph}$) if it is constructed, plus the biobutanol inventory level at the end of period$t-1$ ($INVB_{p,t-1,h}$).

$$\sum_{e=1}^{E} \sum_{r=1}^{R} TRB_{phert} \leq capb_p YB_{ph} + INVB_{p,t-1,h} \ \forall p,\ t,\ h \tag{16}$$

Eq. (17) is built to satisfy the demands. All transported biobutanol from butyryl coa workstations p in biobutanol refinery plants ($\sum_{p=1}^{P} \sum_{h=1}^{H} \sum_{r=1}^{R} TRB_{phert}$) must fulfill the demand of every customer e in period t (d_{et}).

$$\sum_{p=1}^{P} \sum_{h=1}^{H} \sum_{r=1}^{R} TRB_{phert} \geq d_{et} \ \forall e,\ t \tag{17}$$

Eq. (18) ensures until every biobutanol refinery plant h has not been constructed, a pyruvate workstation in biobutanol refinery plant h cannot be installed. Also, if biobutanol refinery plant h has constructed, only one type of pyruvate workstations can be constructed.

$$\sum_{l=1}^{L} YP_{lh} \leq Y_h \ \forall h \tag{18}$$

Eqs. (19)–(21) ensure that, whether a biobutanol refinery plant h is constructed, only a type of workstations can be built in each plant.

$$\sum_{m=1}^{M} YA_{mh} = \sum_{l=1}^{L} YP_{lh} \ \forall h \tag{19}$$

$$\sum_{n=1}^{N} YAC_{nh} = \sum_{m=1}^{M} YA_{mh} \ \forall h \tag{20}$$

$$\sum_{p=1}^{P} YB_{ph} = \sum_{n=1}^{N} YAC_{nh} \ \forall h \tag{21}$$

Eqs. (22)–(27) ensure that there is no inventory in period $t=0$ in all sections of the supply chain.

$$INVD_{j,0} = 0 \ \forall j, t = 1 \tag{22}$$

$$INVZ_{k,0} = 0 \quad \forall k, t = 1 \tag{23}$$

$$INVP_{l,0,h} = 0 \ \forall l, t = 1, h \tag{24}$$

$$INVA_{m,0,h} = 0 \ \forall m, t = 1, h \tag{25}$$

$$INVAC_{n,0,h} = 0 \ \forall n, t = 1, h \tag{26}$$

$$INVB_{p,0,h} = 0 \ \forall p, t = 1, h \tag{27}$$

$$YH_i, YD_j, YZ_k, Y_h, YP_{lh}, YA_{mh}, YAC_{nh}, YB_{ph} \in \{0, 1\} \tag{28}$$

$$\text{All countinios variables} \geq 0 \tag{29}$$

4. Fuzzy model

We live in an uncertain world that nothing can be predicted confidently. A major part of the real world decision-making is in an environment where the goals, constraints, and consequences of possible actions are not clear accurately. Fuzzy programming method usually works with uncertainties that historical data is not available about them and an interval can be considered for data with a variation of probabilities. Due to the lack of historical data about harvesting and drying algae in Iran, the fuzzy approach is suitable for this problem.

The fuzzy set theory was utilized to solve optimal decision-making problems [52]. Zimmermann [53] developed fuzzy programming to accommodate multiple objective functions by linear programming. The membership function of fuzzy models can well describe them. These membership functions indicate each goal. Minimum, maximum, trapezoidal, and triangular are the names of four kinds of fuzzy membership functions [54]. The goals which their lower values are more favorable, are defined as minimum membership function of the fuzzy sets. In contrast, the goals which their higher values are more favorable, are defined as the maximum fuzzy membership functions. The trapezoidal fuzzy membership function is defined for the goals which have limited values in a definite objective range. Finally, the triangular fuzzy membership function is a special kind of trapezoidal membership function of the fuzzy sets [34].

Kornbluth and Steuer [55] presented some treatments of constraints by necessity and possibility concepts. The possible degree of an event is equal to or greater than its probability degree, that itself must be equal to or greater than its necessity degree [56]. Necessity and possibility are utilized to create solutions [57]. They are defined as follows:

$\Re$ is a set of real numbers and a fuzzy subset $\tilde{a}$ of $\Re$ which have the membership function $\mu_{\tilde{a}} : \Re \rightarrow [0,\ 1]$ named a fuzzy number. $\tilde{a}$ is considered a fuzzy quantity with membership function $\mu_{\tilde{a}}$ Similarly, $\tilde{b}$ is considered a fuzzy quantity with membership function $\mu_{\tilde{b}}$ The abbreviation *Pos* and *Nes* illustrate possibility and necessity, respectively. Besides $*$ demonstrates any one of the relations $\leq,\ \geq,\ =,\ <,\ >$ [58,59].

$$Pos\left(\tilde{a}*\tilde{b}\right) = \sup\left\{\min\left(\mu_{\tilde{a}}(x),\ \mu_{\tilde{b}}(y)\right),\ x,\ y\in\Re, x*y\right\} \tag{30}$$

$$Nes\left(\tilde{a}*\tilde{b}\right) = 1 - Pos\overline{\left(\tilde{a}*\tilde{b}\right)} \tag{31}$$

Since the volume of harvested algae and dried algae are not precisely in the real world, the fuzzy approach is applied to address these uncertainties. For instance, weather conditions such as temperature, humidity, etc. affect the volume of harvested and dried algae, directly. Therefore, the fuzzy approach is employed to deal with these uncertain parameters. For this reason, a triangular fuzzy number $\tilde{\xi}$ has been defined for harvested algae which have three members ξa, $\overline{caph_i}$, and ξb with membership degrees $\{\mu_1,\ \mu_2,\ \mu_3\}$. Also β and θ alluded to the confidence levels. In a general formulation for an uncertain constraint like $r \leq \tilde{\xi}$, a certain constraint can describe it as below [13]:

$$r \leq \beta\xi a + (1-\beta)\overline{caph_i} \tag{32}$$

$$\sum_{j=1}^{J}\sum_{r=1}^{R} TRH_{ijrt} \leq \left(\beta\xi a_i + (1-\beta)\overline{caph_i}\right) YH_i \ \forall i,\ t \tag{33}$$

In this way, constraint (10) that includes the exact volume of harvested algae is reformulated as follows.

Likewise, a triangular fuzzy number $\tilde{\lambda}$ has been defined for dried algae which have three members λa, $\overline{capd_j}$, and λb with membership degrees $\{\vartheta_1,\ \vartheta_2, \vartheta_3\}$. In this way, constraint (11) that includes the exact volume of dried algae is reformulated as follows:

$$\sum_{k=1}^{K}\sum_{r=1}^{R} TRD_{jkrt} \leq \left(\theta\lambda a_j + (1-\theta)\overline{capd_j}\right) YD_j + INVD_{j,t-1} \ \forall j,\ t \tag{34}$$

Other constraints are repeated because they do not have uncertainty and all parameters of them are deterministic.

5. Case study

The proposed model of this study is utilized to design an algal biobutanol supply chain in Iran. Development of algal biofuel in Iran can have multiple motivations; such as: (1) wide lands which are not appropriate for agricultural actions; (2) The existence of different weather conditions in Iran at any time of year by which biomass can be continuously produced; (3) abundant sunshine; and (4) Reducing non-renewable resources [60].

According to the proposed model, an approach of DEA is used in order to rank places based on efficiency for harvesting microalgae. This can help us to ignore some non-efficient places to reduce the complexity of computations and selecting efficient areas. Ranking in the DEA has different types which are categorized as cross-efficiency, multi-criteria decision making, inefficient DMUs, super-efficiency, benchmark, multivariate statics, and multi-criteria decision making [61].

In this research, the cross-efficiency evaluation is used because it provides an exceptional ranking of the DMUs. In addition, it obliterates unrealistic weight structures without the need for antecedent data on weight limits. Let DMU k 'choose' its own weights v_{ky} (for k's yth output), and u_{kx} (for k's xth input). The cross-efficiency of DMU s, using the weights that k has chosen, is then [62]:

$$maximize\ E_{kk} = \sum_y O_{ky} v_{ky}$$

Subject to:

$$u_{kx}\ and\ v_{ky} \geq 0$$

Table 6
Introduction of areas.

Sign	Area	Sign	Area	Sign	Area	Sign	Area
1	Chabahar	12	Dezful	23	Urmia	34	Yasuj
2	Ahvaz	13	Sari	24	Ilam	35	Qazvin
3	Jask	14	Gorgan	25	Zabol	36	Ardabil
4	Bandar Abbas	15	Yazd	26	Chalus	37	Birjand
5	Bandar-e Mahshahr	16	Kermanshah	27	Mashhad	38	Qom
6	Bandar Lengeh	17	Bam	28	Zanjan	39	Bojnurd.
7	Shiraz	18	Rasht	29	Khorramabad	40	Semnan
8	Bushehr	19	Tabriz	30	Sanandij	41	Maku
9	Tehran	20	Shahr-e Kord	31	Sabzevar	42	Tabas
10	Bandar Kangan	21	Gonband-e Kavus	32	Arak	43	Hamadan
11	Isfahan	22	Zahedan	33	Kerman		

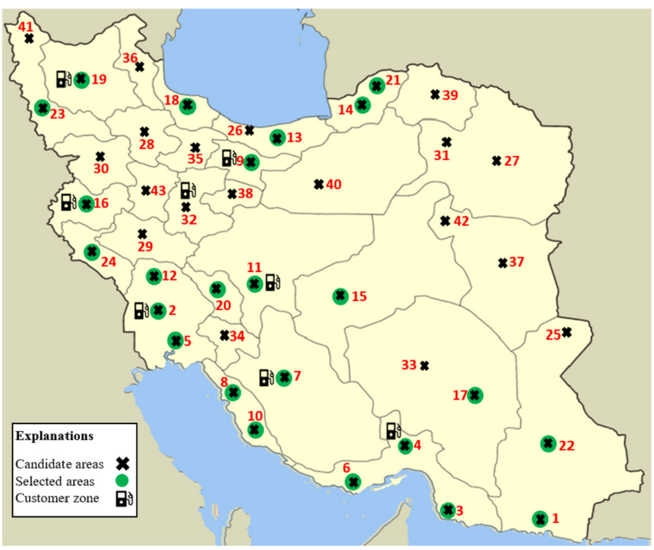

Fig. 2. Selected areas using DEA.

Table 7
Customer zone.

Sign	Area	Sign	Area
2	Ahvaz	11	Isfahan
4	Bandar Abbas	16	Kermanshah
7	Shiraz	19	Tabriz
9	Tehran	32	Arak

Table 8
Parameters value.

Parameter	Considered value
β	0.95
θ	0.95
γ	0.22
ψ	1
φ	1
τ	0.667
α	0.756
δ	0.827

$$E_{ks} \leq 1 \; for \; DMUs \; s, \; including \; k$$

$$\sum_x I_{kx} u_{kx} = 1$$

In the case study in order to reach the cities in which the best circumstances are available, 43 cities (see Table 6) are considered for suggested locations with 4 different capacities for workstations. Using DEA approach, 24 cities are selected owning to have more logical answers for harvesting microalgae (see Fig. 2). For using this approach we had different DEA factors such as light, low and the high temperature of every area, resource availability, and joblessness ratio of every area. Necessary information for these factors is gained from relevant websites including www.irimo.ir, www.isna.ir, www.eghtesadonline.com, and expert judgments in this field. 8 customers are considered for consuming biobutanol as illustrated in Table 7. Two kinds of transportation modes are considered in this case study including rail and road transportations. The parameters which have been introduced in section 3 are obtained from the database websites such as Statistical Center of Iran (www.amar.org.ir), and markets in Iran.

Some of the important parameters are categorized in Table 8. As mentioned in Milledge and Heaven [51] research, γ can vary from 0.5 to 27% and considering this case study situation γ took 0.22. Likewise, Bevan [63] has proposed the metabolic pathway of ABE fermentation process and mole percentages of carbon end products. Thus, considering the proposed percentages in her work, ψ,φ,τ, α, and δ are calculated as illustrated in Table 8. Besides.

β and θ are usually considered 0.95. The planning horizon is considered 25 years in this case study that is broken up into 100 three-month periods. This planning horizon is long sufficient to justify the input investment. Also, three months can enable the model to consider seasonal variability in growth of microalgae.

Considering the aforementioned points, the candidate areas and selected areas are indicated in Fig. 2. It can be concluded that most of the selected areas are near coasts and humid areas sensitivity analysis is performed in order to understand the effects of parameter changes on the objective function. Fig. 3 shows that objective function and demand are directly related, and as the demand increases, the objective function rises significantly. As demand increases, total operational costs such as manpower, electricity and energy costs will increase. Therefore it can be the reason for raising the objective function. For example, if demand increases by 10%, the objective function will increase by 12%.

According to financial fluctuations in Iran, it is better to do the sensitivity analysis on parameters which relate to costs. For this very reason, it is a good idea to analyze cost parameters sensitivity for considering objective function changes. It is because altering cost parameters can have a major effect on total cost that can make the proposed model inefficient, economically. Thus, transportation and operational costs are analyzed in an interval of [-50%, +50%] to have a good insight into the membered problem.

As illustrated in Fig. 3 changes in operational costs have a weak effect on objective function. By increasing operational costs as much as 50%, the objective function only increases 9%. There are

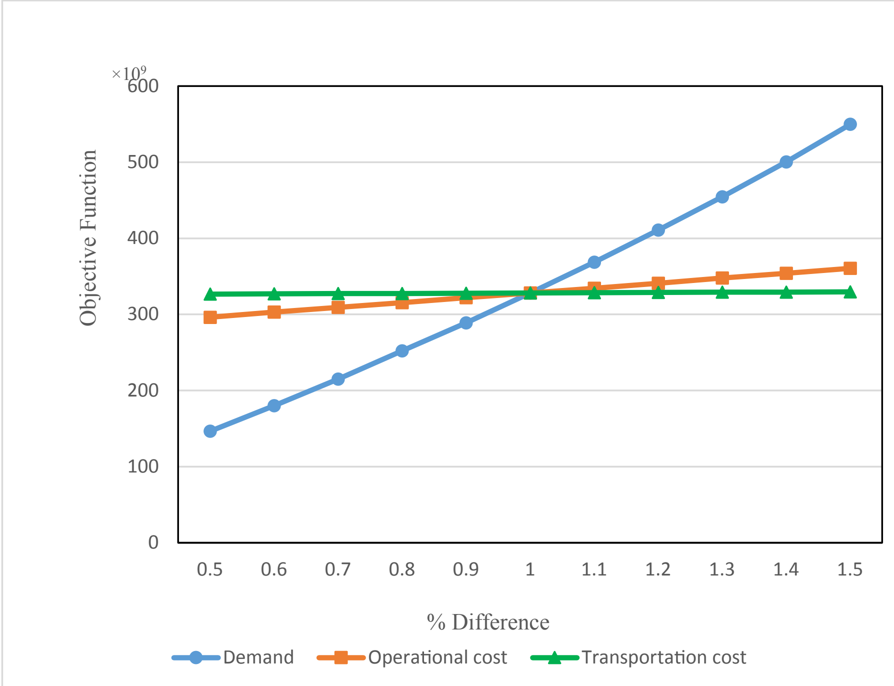

Fig. 3. Effect of demand, operational cost, and transportation cost on the objective function.

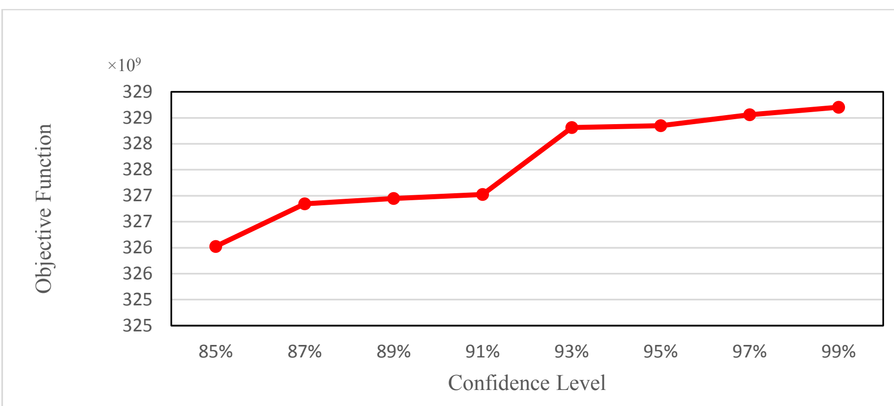

Fig. 4. Effect of confidence level on the objective function.

low energy cost and worker wage in Iran. Thus, operational cost includes a small portion of total cost. That is why changing operating costs has hardly any effect on the total cost. Likewise, analyzing transportation cost sensitivity shows that the changes in transportation cost parameters have a weak effect on objective function. Due to low the fuel and transportation cost in Iran, the weak effect on objective function is acceptable. For example, the objective function rises only 0.3% by increasing transportation costs 50%.

It is clear that the objective function will increase by enhancing the confidence level. Precisely speaking, if the risk effects decrease, the costs will rise notably (Fig. 4). Another evidence which indicates the validity of the addressed model is choosing the suitable areas. Fig. 5 shows the areas which have been selected for harvesting location. It is noteworthy to mention that the model has chosen the areas with humid weather in the south of Iran and Golestan in the north, adjacent to the sea. But surprisingly, it has not chosen Sari and Rasht in the north of Iran which are next to the sea. This can be justified by capital requirement per production unit. For instance, by comparing Bandar Lengeh which is chosen for harvesting and Sari which is not chosen, Bandar Lengeh has a more suitable condition. Because there is cold weather in Sari in winter and it is necessary to use heating devices. In contrast, there is always warm weather in Bandar Lengeh. Thus, the cost in Bandar Lengeh is lower. Isfahan has been selected in the center of Iran by virtue of its desirable geographical location, and other cities have not been elected because of their cold and dry weather conditions and their inappropriate geographical location. The government can encourage the agricultural sector of selected harvesting areas by giving subsidy to farmers to cultivate algae. For instance, farmers in the southern areas are cultivating dates but encouraging them to cultivate algae has financial benefits.

Fig. 6 shows that just 3 areas are selected for drying locations because it is considered the high capacity for drying facilities. Since

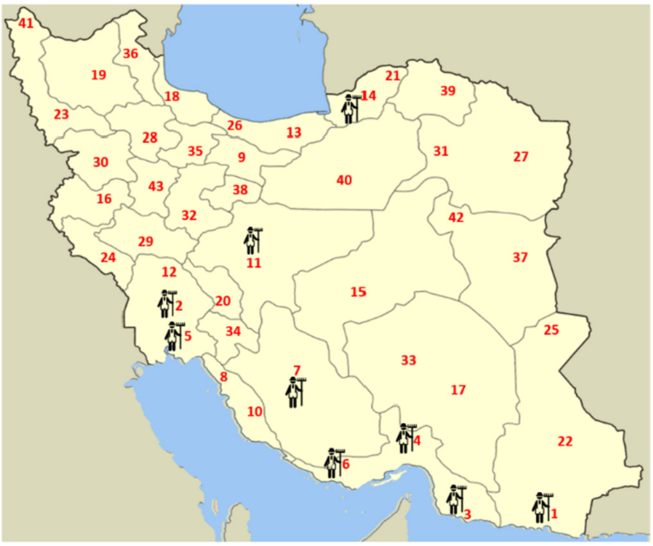

Fig. 5. The selected locations for harvesting microalgae in Iran.

Fig. 7. The selected locations for hydrolyzing dry microalgae in Iran.

Fig. 6. The selected locations for drying microalgae in Iran.

Fig. 8. The selected locations for biobutanol refinery plant in Iran.

they do not have a particular process, each drying plant has the ability to cover several harvesting sites. Therefore a few areas are chosen and they can provide the whole country need.

And Fig. 7 shows the selected areas for constructing hydrolyzing locations. Training and necessary skills for hydrolyzing should be prepared in selected areas. Finally, it can be concluded from Fig. 8 that biobutanol refinery plants are constructed in 23 areas of Iran. It is considered the low capacity for refinery plants due to economic limitations of investigating for constructing a plant in Iran because of technology costs. Hence, many biobutanol refinery plants have to build to meet customer demand. Scientific centers and research and development (R&D) of this type of refineries should be enabled for developing their capacities. Thus, there would be low number of refineries with high capacities which help to better management.

There are some areas in which none of the facilities are constructed (such as 8, 9, 13, 15, 16, 17, 21, 22, 25, 28, 30, 36, 39, and 42) (see Fig. 9). These are poor areas that suitable conditions should be created for them. Alternate fuel can be used in order to convert them into rich areas. Precisely speaking, the agricultural industry can be strengthened or growing the plants which are suitable for the climate of those areas. By doing so, other generations of energy can be used in Iran, such as the second generation. For example, Jatropha can be cultivated in Iran to produce biofuels by using it. There are some areas as shown in Fig. 9 in which all of the facilities have been constructed except one facility (such as 1, 4, 11, 14, 20). The infrastructure of those facilities that they are not constructed should be provided for making these areas as poles. It means that these areas have hub potential.

As is shown in Fig. 9 Jask is the richest area in which all of the facilities can be constructed. Jask can be a hub and by virtue of being a harbor, it also has export potential.

Finally, in order to show that the solution will change significantly if uncertainty was not considered in the proposed model, we have generated sample data using Monte Carlo simulation for parameters$scaph_i$ and $capd_j$ and investigated the objective function results for 26 times. Also, we considered a penalty for lost demands. The gained results average of the deterministic model and

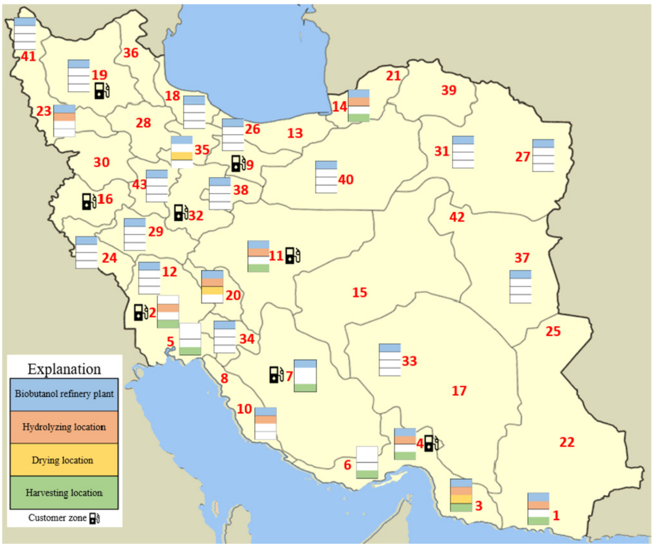

Fig. 9. Harvesting, drying, and hydrolyzing locations and biobutanol refinery plants selected for Iran.

uncertain model are 331,335,153,846 and 313,876,038,696, respectively. The results demonstrate that the uncertain model is better than the deterministic one and we benefit from 17,459,115,150.

6. Conclusion

This paper has proposed an MILP model for planning and designing of microalgae-based biobutanol supply chain network. The presented model minimizes the entire costs of the mentioned supply chain. It is noteworthy to mention that only fossil fuels are used for transportation in Iran. Consequently, greenhouse gasses are increasing rapidly. In this regard, alternative fuels are needed in Iran.

By virtue of the inherent characteristic of microalgae and multiple motivations about algal biofuel in Iran which were mentioned above, this study has spoken about the supply chain of biobutanol from microalgae, and a case study is implemented to demonstrate the applicability of the proposed model in Iran. Since the volume of harvested and dried microalgae is not deterministic, a fuzzy model is employed to address these uncertainties. Due to the dynamic economic condition in Iran, sensitivity analysis is done on economic parameters and demand for the feasibility of the presented model. Both deterministic and fuzzy model are presented under realistic assumptions. The results show the validity and usefulness of the proposed model. It is gained a practical supply chain design model by selecting appropriate and accurate candidate areas. Also, using DEA approach reduced the complexity of choosing many candidate areas for harvesting microalgae.

The results can help managers and policymakers to take suitable strategic level decisions about algae-based biobutanol supply chain network design. As illustrated in the case study there are some cities which are expected to be chosen but the model does not choose them, surprisingly. Thus, various factors are involved in this decision such as different capital requirement per production unit in each area. Also, it is concluded that the objective function is more sensitive about demand changes comparing transportation and operational costs changes. So that, by increasing operational costs as much as 50%, the objective function only increases 9% and operational cost includes a small portion of total cost.

Considering the realization of deterministic and fuzzy models, the average objective function values of the fuzzy model are lower than deterministic ones which shows the validity of the presented model. Since the model is reasonable by changing the parameters, it can be utilized in Iran.

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