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Measuring the Importance of Decision-Making Criteria in Biofuel Production Technology Selection

Siamak Kheybari, Fariba Mahdi Rezaie, and Jafar Rezaei

***Abstract*—Environmental problems, combined with a finite supply of fossil fuels, have made the use of renewable energy sources necessary. Biomass is a renewable source of energy that has played a very important role in energy production in recent years. Because there are a number of technologies that can be used to convert biomass into energy, it is important to select the best option. The fact that multiple options are available that need to be evaluated based on a set of decision-making criteria makes this a multicriteria decision-making problem. This paper takes the first step in proposing an evaluation framework and identifying the importance of the relevant decision-making criteria in biofuel production technology selection. To determine the importance of the selection criteria, experts were asked to respond to an online questionnaire based on the best–worst method. The results indicate that air pollution, land use change, and human expertise are the three most important criteria for selecting the best biofuel production technology in our case country, Iran.**

***Index Terms*—Best–worst method (BWM), biofuel production technology, biomass, renewable energy, sustainability assessment framework.**

I. Introduction

POPULATION growth, lifestyle changes, and increased life expectancy and living standard have led to an increase in global energy demand [1], which, in turn, has put a strain on the use of fossil fuels [2], for one thing because of issues related to global warming as a result of increased concentrations of greenhouse gases, e.g., carbon dioxide (CO_2) and methane [3], as a result of using fossil fuels, creating, among other things, acid rain, and causing climate change, environmental degradation, and reduced crop yields [4].

In response to these conditions, renewable energy was introduced as a future source of energy, which not only reduces our dependence on fossil fuels, but also has a positive impact on the economy, the environment, and society [5]. Among the renewable sources of energy, biomass has received considerable attention in recent years, for reasons including its availability, its ability to help reduce greenhouse gas emissions, and its flexibility in the production of a wide range of products [2], [6].

In the last decade, biomass has become the fourth largest source of energy in the world, accounting for 10–14% of overall energy consumption [7]. It is a renewable source of energy that uses degradable agricultural waste (including plants and animal materials), forests, and industrial and urban waste. Biomass is used to produce electricity, heat, liquid fuels, gas fuels, and a variety of useful chemicals [4], [8]. The production of biofuel from biomass also reduces the production of carbon dioxide [9], while preserving nonrenewable resources, generating regional progress and employment, and bringing revenues to underdeveloped areas [8], [10]. On the other hand, there are some disadvantages associated with energy production from biomass. The high cost in its production and supply [11], including labor cost and transportation cost, the need for large spaces for cultivation and storage [12], and the high amounts of water used in biomass cultivation [13] are among the most important disadvantages.

There are various technologies available for converting biomass into energy, and selecting the best option depends on a number of factors, while choosing the wrong one can lead to a number of unwanted direct problems, for people as well as the environment [14]. The literature review reveals that, although there are different criteria that can be used in selecting the right technology, there is no sustainable comprehensive framework that includes them all. Such a framework is needed, because the number of criteria involved in selecting the right technology, which will affect society as well as the environment, could be overlooked in the absence of a proper framework. This research presented the first time comprehensive sustainable framework, which is the main contribution of this paper. The framework makes it possible to assess technologies in different areas, like energy and production, based on criteria that are divided into economic, social, and environmental categories.

In this paper, the proposed framework is used to determine the importance of effective criteria regarding the biofuel production technologies in Iran, a country with extreme levels of air pollution. There are considerable biofuel resources in Iran, for instance, with a potential for bioethanol production of about 4.91 GL [15], while the country's food industry can produce 81.5–279.4 million m^3 of biogas [16]. Moreover, 0.84 million tons of sugarcane, the raw material for gasification, is produced in Iran each year [17], and about 3700 m^3 of oil is consumed each year, 721 000 m^3 of which can be produced as biodiesel [15], [18]. The biomass of Iran's forests is 133 000 000 m^3, which is

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a suitable amount when talking about biomass combustion [15]. To evaluate the criteria presented in the framework, a recently developed multicriteria decision-making (MCDM) method, called the best–worst method (BWM) [19], was used to examine data from an online questionnaire among experts working and studying in the area of biofuel in Iran. The main factors affecting the selection of biofuel production technologies in Iran were identified by analyzing the survey results.

The rest of this paper is organized as follows. The literature review is presented in Section II, after which the methodology is described in Section III. The data collection process and the situation in Iran in terms of biomass resources are discussed in Section IV. In Section V, the effective criteria for the selection of biofuel production technology in Iran are analyzed. Section VI concludes this paper.

II. Literature Review

MCDM papers in different areas of technology selection were reviewed to determine the criteria that influence energy production technologies involving biomass. To identify the papers, different databases were searched. The papers were initially screened on the basis of their title, abstract, and keywords. We used the text and tables of the studies to extract the criteria and divide them into the three dimensions of sustainability: economic; environmental; and social. The findings of the studies are summarized in Table I. The framework and MCDM methods can be used to determine the effect of each criterion in the technology selection. Because the studies on energy production technology were closely related to this paper, they are discussed below.

Searcy and Flynn [20] examined the use of four biomass processing technologies in Canada in terms of field costs, transportation, and processing cost, calculating the overall processing costs for each biomass resource and the production costs, which is a function of the size of the power plant in question, for each technology. Ultimately, the most suitable technology, biomass-integrated air gasification and combined cycle production of electricity, was identified as being the least costly alternative. Oberschmidt *et al.* [21] examined energy supply technologies in Germany, using the preference ranking organization method for enrichment evaluations to rank the alternatives, and identifying profitability, electric efficiency, availability, electricity cost, and maturity as the main criteria, and concluding that a combination of wind, photovoltaic, and gas-condensing boiler provides the best alternative. Amer and Daim [22] conducted a study in Pakistan to select the best electricity generation technology based on renewable resources, using 20 criteria, divided into economic, technical, social, environmental, and political categories and applying the analytical hierarchy process (AHP) to select the best technology, concluding that biomass and wind are the best alternatives. Capital cost, operation and maintenance cost, electricity cost, greenhouse gasses emissions, and land requirement are among the most important criteria in this research. Dapkus and Stremikiene [23] evaluated electricity generation technologies in Lithuania using multiobjective optimization by ratio analysis (MULTIMOORA). They ranked 33 alternatives based on 13 criteria divided into economic, environmental, and social categories, identifying hydro and solar power systems as the most sustainable technologies. Grid costs, availability factor, human health, food safety risks, greenhouse gasses emissions, and job opportunities are some of the main criteria the authors identified. Streimikiene *et al.* [24] developed an MCDM support framework for selecting the best electricity production technologies in Lithuania, using a combination of MULTIMOORA and the technique for order of preference by similarity to ideal solution (TOPSIS). They identified investment and operation cost, security of supply, costs of grid connection, human health impact, job creation, and food safety risk as the main factors in the selection of electricity generation technology, concluding that hydro and solar power systems are the best alternatives. Kempegowda *et al.* [25] examined different technologies for converting biomass into energy in Norway using a technoeconomic approach, based on five criteria divided into technical and economic categories. The results indicated that the efficiency of technologies involved depends on factors like resource availability, reliability, investment cost, and type of fuel, concluding that, in Norway, municipal solid waste combustion, biogas engine, and industrial backpressure turbines were the most profitable technologies.

Stein [26] developed a model for ranking renewable and nonrenewable electricity production in the United States technologies using AHP, ranking alternatives on the basis of ten criteria divided into four categories (financial, technical, environmental, and socioeconomic/political), concluding that wind and solar technologies were the preferred options. Sliogeriene *et al.* [27] selected the best renewable energy production technology (REGT) in Lithuania using AHP and additive ratio assessment methods, examining a set of economic, environment protection, technological, social, ethical, and institutional criteria (such as economic efficiency, effect on climate change, production costs, and energy prices), concluding that biomass was the best alternative of the four renewable energy generation technologies they evaluated.

Demirtas [28] used AHP to identify the best renewable energy technology for sustainable energy planning in Turkey, assessing the technologies on the basis of 12 criteria divided into technical (technology maturity, reliability energy production, and safety), economic (investment cost, operation and maintenance cost, payback period, and service life), environmental (impact on ecosystem and CO_2 emission), and social (social benefits and social acceptability) categories, the results indicating that wind energy is the most appropriate renewable energy alternative. Ren *et al.* [29] examined four biomass-based technologies based on technical, economic, environmental, and social–political criteria, using the fuzzy multiactor MCDM method, the results showing that biomass gasification is the best alternative. Capital cost, production cost, energy efficiency, land use, maturity, reliability, social acceptability, and job creation are among the main criteria used in the assessment. Tang *et al.* [30] conducted a study to select key technologies related to silicon solar cells in China, after reviewing relevant literature and examining the available technologies and the criteria used to select them, after which they used the Delphi and AHP methods to determine the importance of the various attributes and rank the technologies. Operational cost, energy consumption cost, required floor space, and energy

TABLE I
SUSTAINABLE FRAMEWORK FOR BIOFUEL PRODUCTION TECHNOLOGY SELECTION

Dimension	Criteria	Sub-criteria	References
Environmental	Water pollution		[38, 42, 43]
	Water use		[38, 44]
	Energy losses		[30, 44, 45]
	Air pollution		[8, 22-24, 27, 28, 34-38, 40-42, 44-55]
	Noise pollution		[40, 52, 55]
	Need of waste disposal		[37, 42, 44, 47]
	Soil quality degradation		[38]
	Land use change		[38, 46]
	Biological diversity loss		[38]
Social	Social impacts		[43]
		Social benefits	[22, 28, 38, 44, 50, 53, 56]
		Effect on food security	[23, 24, 38, 41, 46]
		Ease of conforming with health and safety	[28, 40-42, 52, 57]
		Engineering companies	[37]
		Job creation	[22-24, 26, 27, 29, 36, 38, 41, 44, 46, 50, 52, 53, 55]
		Cooperation capability	[32]
		Contribution to economy	[49, 53]
	Social acceptability		[8, 22, 28, 29, 34, 36, 40, 46-49, 52, 55]
	Human resource impact		[23, 24, 34, 37, 47, 58, 59]
		Expert human resource	[22, 54, 60]
		Workers involvement	[60]
		Training employees	[60]
		Technology complexity and amount of utilization convenience of materials	[24, 27, 37, 54, 56]
	Policy and legal support		
		Political acceptance	[8, 22, 27, 29, 38, 39, 47, 48, 53]
		Contribution to the energy sufficiency	[50, 53]

TABLE I
CONTINUED

Dimension	Criteria	Sub-criteria		References
Economic	Investment cost			[22, 24, 25, 28-30, 32, 34-37, 40-42, 44, 45, 47, 52, 53, 55, 56, 58-62]
		Technology cost		[25, 27, 39, 42, 47, 52, 63, 64]
		Land requirement		[22, 29, 34, 36, 38, 47, 49, 52, 55, 58, 60]
		Incentives and subsides		[27, 37, 52, 55, 57]
		Infrastructure availability		[48]
		Risk		[39, 47, 52, 55, 62-67]
		Durability		[27, 54]
		Costs of grid connection		[27]
	Operation and production cost			[22, 24, 26, 28, 32, 36, 40-45, 52, 54-57, 61]
		Maintenance cost		
			Market stability for equipment support	[37, 39, 64, 65]
			Number of machine tools	[37, 60]
			Warranty issues	[32, 37]
		Electricity cost		[21, 22, 25, 26, 35, 40, 42, 45, 68]
		Raw material cost		[45]
		Labor cost		[60]
		Climate condition		[27, 37, 46]
	Productivity			[44, 59, 60]
		Product Flexibility		[37, 42, 44, 47, 57-59, 61, 67]
		Flexibility (Versatility)		[37]
		Production time (Timing of entry)		[60] [39, 47, 56]
		Set-up time		[22, 27, 37, 40, 44, 47, 55, 60, 66, 69]

TABLE I
CONTINUED

Dimension	Criteria	Sub-criteria	References
		Capacity factor, Scale of operation, Production volume	[32, 37, 48, 55]
		Reliability	[22, 27-29, 32, 43, 44, 46, 47, 49, 52, 53, 57, 59, 63]
		Lower defect rates	[28, 42, 63]
		Process efficiency	[23, 27, 30, 34-37, 40, 42, 52, 53, 55, 62]
		Operational supremacy	[39]
		Technological superiority	[39]
		Compatibility	[39]
		Complementary goods	[39]
		Operability of the emergency disposition	[56]
		Value of waste quality	[54]
	R&D cost		[22, 63]
		Technology development potential	[39, 57]
		Potential for innovation to lead to more competitive and secure bioenergy chains	[8, 27, 60, 64-66]
	Distribution and sales		[39]
		Distribution strategy	[39]
		Marketing communications	[39]
		Pricing strategy	[39]
	Logistic		
		Distribution grid availability	[22, 23]
		Lead time reduction	[57, 58, 60]
		Resource availability	[8, 22-24, 29, 32, 34, 37, 39, 54-56, 60, 65]
		Security and stability of bioenergy supply chains	[8, 21, 23, 37, 41, 66]
	Profitability		[60, 65]

TABLE I
CONTINUED

Dimension	Criteria	Sub-criteria	References
	Payback period (PP)		[34, 44, 52, 55, 61, 65, 67]
	Economic viability in the market		[8, 28, 53]
	Net Present Value (NPV)		[25, 34, 52]
	Technology maturity		[22, 28, 29, 34, 37, 38, 49, 53, 55, 63]
	Internal rate of return (IRR)		[25, 47, 52, 63, 64]

efficiency were among the criteria they applied. The results gave solar-grade silicon production the highest score among 43 technologies.

Lanjewara *et al.* [31] used an integrated diagraph method and AHP to select and rank solar energy technologies in India, evaluating alternatives on the basis of seven criteria, divided into technological, economic, social, and political categories, with the Box Carrier (batch) process emerging as the best alternative. Onar *et al.* [32] determined the best technology for producing wind energy in Turkey, based on eight indicators—reliability, technical characteristics, performance, cost factors, availability, maintenance, cooperation, and domesticity—using a multiexpert MCDM model and the interval-valued intuitionistic fuzzy set approach to prioritize four technologies, with WTE82 proving to be the best alternative.

Buyukozkan and Guleryuz [33] used a combination of fuzzy AHP and fuzzy TOPSIS to identify the best REPT in Turkey, based on 12 criteria, divided into technical, economic, social, and environmental categories, identifying investment cost, return on investment, job creation, efficiency of technology, and reliability as the main criteria. The results showed that nuclear energy was the best alternative. Cánovas-Rodríguez *et al.* [34] selected the optimal renewable energy technology for electricity generation in Spain, using fuzzy AHP. Land requirement, social acceptance, labor impact, efficiency, resource availability, economic value, and noise proved to be the most important criteria in their study, identifying wind energy as the best alternative for electricity generation. Lanjewar *et al.* [35] used the integrated graph theory AHP method to choose between renewable energy technologies in India. Their study identified efficiency, electricity costs, investment costs, and CO_2 emission as the main criteria for ranking the alternatives, with nuclear power plants emerging as the best alternative. Abdullah and Najib [36] used intuitionistic fuzzy AHP for REPT selection in Malaysia, assessing the different technologies on the basis of nine criteria divided into technical, economic, environmental, and social categories, again with nuclear energy proving to be the optimal choice. Cutz *et al.* [37] chose the best biomass conversion technology in Central America. Looking at the specific conditions surrounding biomass supply in each individual country, they applied a fuzzy MCDM method to identify a number of suitable technologies for converting biomass into energy on the basis of technical, economic, environmental, and sociopolitical criteria. Their findings indicated that the most suitable technology in this area would be direct combustion.

Khishtandar *et al.* [38] conducted a study involving bioenergy production technologies in Iran. They started by classifying 15 criteria, divided into environmental, economic, technical, and social categories and then applied the hesitant fuzzy linguistic term sets method to rank the technologies; their findings indicated that biogas and biodiesel were the best and worst technologies, respectively. Van de Kaa *et al.* [39] conducted a study involving thermochemical conversion technologies in the Netherlands, assessing the performance of gasification, combustion, and pyrolysis, based on 12 relevant factors that were clustered into four groups (characteristics of the format support, characteristics of the format, format support strategy, and other stakeholders), after which, based on expert opinions and using BWM, the factor weights were calculated and the technologies ranked. The results identified gasification as the best alternative.

Ren [40] conducted a study to select the best sustainable way for combined cooling, heat, and power technologies, using a hybrid methodology combining interval BWM and VIKOR to determine the weights of the evaluation criteria and alternative ranking, respectively, identifying 13 criteria, divided into economic, environmental, technological, and social categories, and concluding that fuel cells provide the most sustainable technology. Yazdani *et al.* [41] used a combination of analytical network process, decision-making trial and evaluation laboratory, weighted aggregated sum product assessment, and complex proportional assessment to identify the best REPT in the European Union member states, using 13 criteria, divided into environmental, social, and economic categories, identifying hydropower technology as the most attractive REGT.

After conducting a comprehensive literature review, we present a comprehensive framework for the selection of biofuel

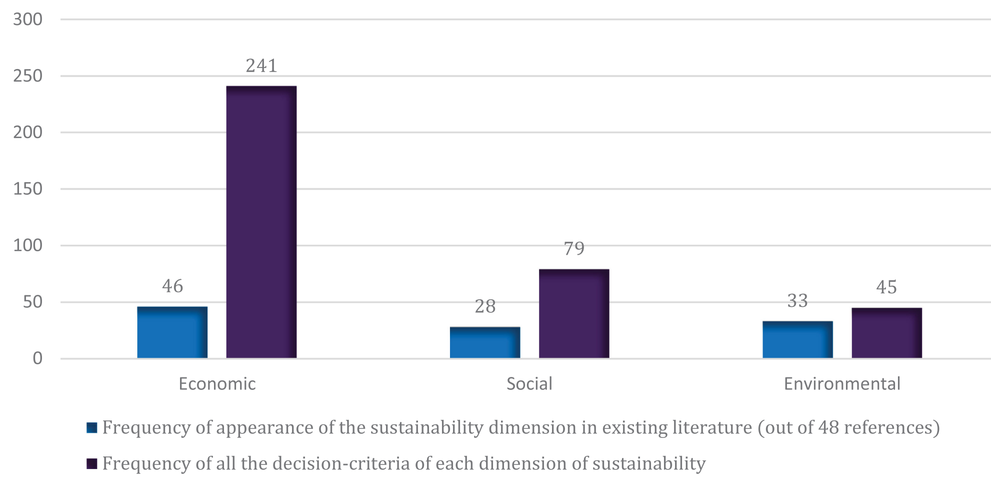

Fig. 1. Frequency of appearance of sustainability dimensions and all their associated decision criteria in existing literature (48 references).

production technology, dividing all the relevant decision-making criteria into three dimensions of sustainability: economic, environmental, and social sustainability (see Table I).

Fig. 1 presents a summary of Table I on the frequency of the appearance of the sustainability dimensions and their associated criteria in existing literature.

As can be seen from Fig. 1, Economic dimension has appeared in almost all studies (46 out of 48), while the other two dimensions, Environmental and Social, have appeared in 33 and 28 studies, respectively. Counting the number of criteria of each dimension appeared in each study, we see that in total, all the Economic-related decision criteria have appeared 241 times in the existing literature, while for the other two dimensions, Environmental and Social, this number is 79 and 45, respectively. This shows that while Economic dimension has received a lot of attention in the existing literature, Environmental and Social dimensions have been largely overlooked.

Of the MCDM methods used in the studies we reviewed, AHP occurred most frequently. However, the BWM, a new MCDM method developed by Rezaei [19], outperforms AHP in several aspects. The BWM: 1) is more consistent than AHP, because the number of pairwise comparisons in AHP is greater than that in BWM, which has a cognitive effect on the evaluator when it comes to analyzing all of the criteria together consistently (BWM requires $2n-3$ pairwise comparisons, compared to $n(n-1)/2$ pairwise comparisons for AHP) [19], [70], [71]; 2) reduces the number of comparisons, thus increasing the return rate for the questionnaire [19], [72]; and 3) only applies integers, making it easier to use [19], [73], [74]. The BWM has been used successfully in different areas, including innovation and technology management [75], [76], supply chain management [77]–[79], and water resource management [80].

III. Best–Worst Method

The BWM, a vector-based method, is the method used in this paper. Determining the weights of the criteria using BWM involved the following steps [1–4 being done by the decision maker(s)] [81].

1) Determine a set of decision criteria $\{c_1, c_2, \ldots, c_n\}$.
2) Identify the best (*B*) and the worst (*W*) criteria.
3) Determine the preference of the best over all the other criteria by a number from 1 to 9 (where 1 is "equally important" and 9 is "extremely more important"). The result of best-to-others comparisons is vector $A_B = (a_{B1}, a_{B2}, \ldots, a_{Bj}, \ldots, a_{Bn})$, where a_{Bj} shows the preference of criterion *B* over criterion *j*.
4) Determine the preference of all the criteria over the worst. The result of others-to-worst comparisons is vector $A_w = (a_{1W}, a_{2W}, \ldots, a_{jW}, \ldots, a_{nW})$, where a_{jW} denotes the preference of criterion *j* over criterion *W*.
5) Compute the optimal weights $(w_1^*, w_2^*, \ldots, w_n^*)$.

The optimal weights are calculated by minimizing the maximum absolute difference of $\{|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|\}$ for all *j*, which is translated into the following optimization problem:

$$\min \max_j \{|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|\}$$

such that

$$\sum_{j=1}^{n} w_j = 1$$

$$w_j \geq 0, \text{ for all } j. \tag{1}$$

Model (1) is converted into:

$$\min \xi$$

such that

$$|w_B - a_{Bj}w_j| \leq \xi, \text{ for all } j$$

$$|w_j - a_{jW}w_W| \leq \xi, \text{ for all } j$$

$$\sum_{j=1}^{n} w_j = 1$$

$$w_j \geq 0, \text{ for all } j. \tag{2}$$

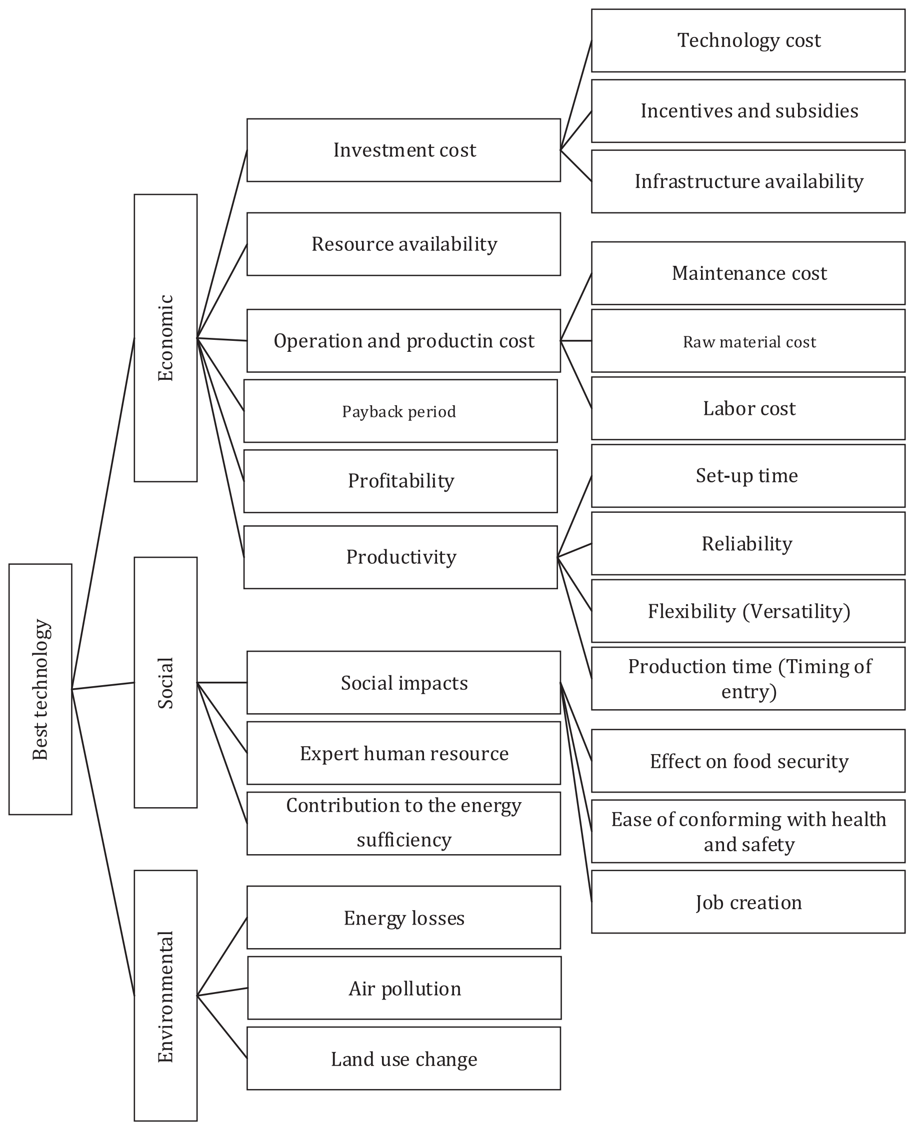

Fig. 2. Hierarchical tree for criteria.

$W^* = (w_1^*, w_2^*, \ldots, w_n^*)$ that is optimal weight of criteria is the result of Model 2. ξ^*, result of the objective function in Model 2, indicates the consistency rate. If ξ^* is close to zero, that means a high level of consistency in the pairwise comparisons provided by the expert(s).

When there is an MCDM problem with more than one level, the results of Model 2 are called local weights. To determine the global weight of subcriteria in the last level of the hierarchical tree, their local weight is multiplied by the weight of the category to which they belong.

IV. Data Collection

In this paper, screening the criteria was the first data collection step. To improve the power of discrimination of the decision maker [82] and the reliability of comparison between criteria [19], the criteria included in Table I were screened using an online questionnaire based on a five-point Likert scale. Seven experts were invited to screen the criteria, after which the criteria with an average value of over 3.5 were retained, while the others were eliminated. The need to maintain a balance among subcriteria [83] was the reason for selecting 3.5 as the cutoff point. Fig. 2 shows the results of the screening process.

A summary explanation of criteria in Fig. 2 is presented in Table II.

The next step involved an online questionnaire based on the criteria shown in Fig. 2, and using the BWM to determine the relative weight of the criteria. In this step, 35 experts were asked for their opinion. Because renewable energy is a new industry in Iran, there were some university and research institute researchers among the people who filled in the questionnaire. All the respondents were identified on the basis of their online profile. Respondents needed to have sufficient knowledge and experience with renewable energy facilities. Of 35 experts involved in this research, 22 (63%), with 7.73 years' work experience, were employed as senior managers in organizations

TABLE II
DEFINITION OF CRITERIA BEING SCREENED

Criteria	Definition
Investment cost	The fixed costs related to each technology
Technology cost	The cost of owning each technology
Incentives and subsidies	The amount of financial support provided by government for each technology
Infrastructure availability	Equipment and facilities that should be provided for each technology
Resource availability	The amount of raw material that is accessible for each technology
Operation and production cost	The costs that have a direct relation to the volume and quality of products
Maintenance cost	The cost related to keeping each technology running
Raw material cost	The cost of raw material used by each technology
Labor cost	The amount of labor cost needed for each technology
Payback period	The length of time required for each technology to compensate its initial cost
Profitability	The degree to which a technology yields a profit
Productivity	Value added/(Inputs)
Set up time	The time required for each technology to start running
Reliability	The length of time that each technology can work at high quality
Flexibility	The variety of products generated by each technology
Production time	The time spent producing a specific number of products by each technology
Social impacts	The different social effect of each technology
Effect on food security	The impact of each technology on the volume of products cultivated
Ease of conforming with health and safety	The effect of each technology on the health of people working with the technology and living in the community
Job creation	The number of jobs created using each technology
Expert human resource	The number of high qualified specialists for working with each technology
Contribution to energy sufficiency	The contributions of each technology to country's energy independence
Energy losses	The amount of energy used by each technology for production of products
Air pollution	The effect of each technology on the air pollution
Land use change	The impact of each technology on the area of land cultivated with biomass

related to energy, like the Niroo Research Institute, Research Institute of Petroleum Industry and Renewable Energy and Energy Efficiency. The remaining 13 (37%) were employed as faculty members, with an average work experience of 11.08 years. Collecting the results of the two steps, screening and weighting the criteria, took seven and 30 days, respectively. After completing and collecting the questionnaires, using the arithmetic mean, expert opinions about the effective criteria on energy generation technology from biomass were collected, and the criteria in the three dimensions were ranked.

V. RESULTS AND DISCUSSION

In this paper, the relevant criteria for selecting technologies for converting biomass into energy and fuel were evaluated based on three categories (economic, social, and environmental). Tables III–V contain the mean and standard deviation of the weights of criteria and subcriteria on levels 1–3, respectively. According to the experts' opinion, economic factors have the greatest effect on technology selection for converting biomass to energy (see Table III). Because Iran is such a major producer of oil and gas [84], most technologies converting biomass

TABLE III
WEIGHTS OF THE MAIN CRITERIA

Criteria	Weight	Standard deviation	Rank
Economic	0.401	0.151	1
Environmental	0.363	0.139	2
Social	0.236	0.110	3

TABLE IV
WEIGHTS OF SUBCRITERIA IN LEVEL 2

Category	Sub-criteria	Weight	Standard deviation	Rank
Economic	Investment costs	0.227	0.071	1
	Resource availability	0.104	0.034	6
	Production and operation costs	0.174	0.060	3
	Payback period	0.165	0.076	4
	Profitability	0.181	0.090	2
	Productivity	0.149	0.059	5
Environmental	Energy losses	0.273	0.121	3
	Air pollution	0.409	0.162	1
	Land use change	0.318	0.162	2
Social	Social impacts	0.259	0.125	3
	Expert human resource	0.423	0.169	1
	Contribution to energy sufficiency	0.318	0.150	2

TABLE V
WEIGHT OF SUBCRITERIA IN LEVEL 3

Category	Sub-criteria	Weight	Standard deviation	Rank
Investment cost	Technology price	0.358	0.173	2
	Incentives and subsidies	0.374	0.169	1
	Infrastructure availability	0.268	0.117	3
Operation and production cost	Maintenance cost	0.347	0.176	1
	Raw material cost	0.340	0.148	2
	Labor cost	0.313	0.139	3
Productivity	Set-up time	0.176	0.079	4
	Reliability	0.262	0.106	2
	Flexibility (Versatility)	0.334	0.139	1
	Production time (Timing of entry)	0.227	0.117	3
Social impacts	Effect on food security	0.242	0.124	3
	Ease of conforming with health and safety	0.419	0.148	1
	Job creation	0.340	0.149	2

into energy have little economic justification, which means that technologies with better economic conditions are more likely to be selected. Economic dimension is usually considered as the main aspect in the selection problem of energy production technologies [85]. The experts weighted environmental and social categories as the second and third most important dimensions, respectively (see Table III).

Similar to the results of the studies by Bouyukozcan and Guleryuz [33], Amer and Daim [22], Kempegowda *et al.* [25], and Si *et al.* [44], *investment costs* were identified as the most influential subcriterion in the economic category (see Table IV), which may be explained by the country's high inflation and by the costs involved in converting biomass into energy [86]. Based on the respondents' point of view, *resource availability* has the minimum weight in technology evaluation (from the economic perspective). As discussed in Section I, the existence of different types of raw material in Iran [87] could explain the low weight of *resource availability. Profitability*, *production and operation cost*, *payback period*, and *productivity* are the other important subcriteria in the economic dimension (see Table IV).

Incentives and subsidies were identified as being the most important subcriterion of investment cost (see Table V), because the government's financial support (including direct grants, seed capital, low-interest loans, loan guarantees, and investment tax credit) in the area of renewable energies reduces the risk of investment [16]. *Technology price* and *infrastructure availability* were weighted as the second and third most important subcriteria in this category (see Table V). Easy access to variety of construction materials in Iran due to the existence of various mines [88] can be considered as a reason to explain the low importance of *infrastructure availability* compared to *technology price.*

Experts identified *maintenance cost* as the main subcriterion in the *operation and production cost* category (see Table V). The difficulty of production process in biofuel industries [89], a lack of experienced staff in Iran [90], and difficulties in gaining access to equipment are the primary reasons why *maintenance cost* was given such a high relative weight. *Raw material cost* and *labor cost* are the other two important subcriteria in this category (see Table V). Both high unemployment rate [91] and high number of university graduates [92] in Iran are two causes, which could lead to the low weight of *labor cost* among the three subcriteria of operation and production costs.

Flexibility (*versatility*) was indicated as being the main subcriterion in the productivity category (see Table V) because using a flexible production technology makes it possible to produce different types of products that meet different customer demands. Since Iran, as a developing country, needs various types of energy, a flexible technology can prove useful. *Reliability*, *production time,* and *setup time* are the other three important subcriteria in this category (see Table V).

Expert staff was indicated as being the chief subcriterion of the social category (see Table IV). Since renewable energy is a new industry in Iran [93], the relatively low number of specialists is a deterrent factor in the selection of biofuel production technology. *Contribution to energy sufficiency* and *social impacts* are the other important subcriteria in the social category (see Table IV). *Ease of conforming with health and safety* was identified as the most important subcriterion of the social impact category (see Table V) because, in some technologies that convert biomass into energy, the amount of methane being released is significant [94]. *Job creation* and *effect on food security* are the other two important subcriteria in this category (see Table V). Existing high volume of agricultural and urban wastes in Iran [95] can be considered as a main reason to explain the low importance of *effect on food security* compared to *job creation.*

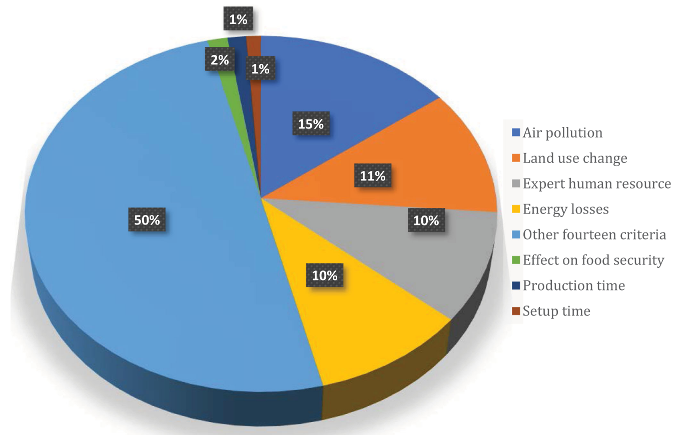

Fig. 3. Importance of subcriteria on technology selection.

Like the studies by Cánovas-Rodríguez *et al.* [34], Amer and Daim [22], and Buchholz *et al.* [46], *air pollution* was selected as the most influential subcriterion by the experts (see Table IV), because of the critical conditions of air pollution in Iran in recent years [96]. According to the environmental performance index, Iran ranks 83rd among 138 countries [97], so any technology that improves air pollution is likely to be preferred. *Land use change* and *energy losses* are the other two important subcriteria in this category (see Table IV).

A. Global Weight of Criteria

Table VI lists the overall weight of the subcriteria that directly affect the selection of biofuel production technology and indicates that *air pollution* is the most important subcriterion when selecting the best technology for converting biomass into energy in Iran (see Table VI).

Air pollution levels in Iran can explain the weight of this subcriterion, as shown in Fig. 3. As a developing country, Iran is the world's third most polluted country, with an annual loss of $16 billion [98]. *Land use change*, *expert staff,* and *energy losses* are the other important subcriteria that, based on the global weight, make up for approximately 31% of all the criteria involving technology selection. The main reason why land use change is considered important may have to do with the fact that agriculture is such a vital sector in Iran's economy [99]. If, instead of growing agricultural products, the land is used to grow biomass, Iran's

TABLE VI
GLOBAL WEIGHT OF SUBCRITERIA

Sub-criteria	Weight	Rank
Air pollution	0.148	1
Land use change	0.115	2
Expert staff	0.100	3
Energy losses	0.099	4
Contribution to energy sufficiency	0.075	5
Profitability	0.073	6
Payback period	0.066	7
Resource availability	0.042	8
Incentives and subsidies	0.034	9
Technology price	0.033	10
Ease of conforming with health and safety	0.026	11
Infrastructure availability	0.0244	12
Maintenance cost	0.0242	13
Raw material cost	0.0237	14
Labor cost	0.022	15
Job creation	0.021	16
Flexibility	0.020	17
Reliability	0.016	18
Effect on food security	0.015	19
Production time	0.014	20
Setup time	0.011	21

economy is bound to suffer irreparable damage. As indicated earlier, due to the shortage of specialists in Iran, any technology that requires fewer specialists has a better chance of being selected. Based on the overall weights, *setup time*, *production time,* and *effect on food security* are three subcriteria that have a minimum impact on which biofuel production technology is selected. *Setup time* also has the lowest weight in the study by Ren [40].

VI. CONCLUSION

The aim of this paper was to assess the effective criteria for biomass energy production technology in Iran. To this end, we started by identifying the criteria affecting the technology selection, by reviewing existing studies, and then organizing them in a sustainable framework of economic, social, and environmental dimensions. In the next step, based on the input from seven experts, the criteria were screened, after which the weights of the resulting criteria were determined using the BWM and input from 35 experts.

According to the BWM results, economic factors turned out to be the most important ones. The subcriteria making up this category approach the various technologies from a different economic perspective. Of the economic subcriteria, *investment cost* was identified as being the most important factor, followed by *production and operation cost*, *profitability*, *payback period*, *productivity,* and *resource availability*. Within the environmental category, *air pollution*, *land use change*, and *energy losses* are the most effective subcriteria, respectively. Furthermore, experts identified *expert staff* as being the most important subcriterion in the social category, followed by *contribution to energy sufficiency* and *social impacts*. Based on the global weight and taking into account Iran's specific conditions, *air pollution* was identified as the single most influential subcriterion.

These results had several implications for scholars and practitioners. For scholars, the proposed framework can be useful in designing and building a proper technology in the near future. Public policy makers in Iran can use the results to meet Iran's future renewable energy needs, while investors can use the results of this paper to evaluate the risk factors and reliability of the technologies involved.

The main limitation of this paper was identifying criteria that affect technology selection. Although technology selection was an important issue, there is no paper that covers different studies in this field. Therefore, a review paper may provide useful information on technology selection. Although we assumed that the criteria in the weighting process are independent of each other, considering the effect of a possible interaction between the different criteria is the second suggestion for future research. Applying the proposed framework to select the most suitable biofuel production technology is the third potential future avenue for research resulting from this paper.

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