

Hybrid multi-criteria decision-making approach to select appropriate biomass resources for biofuel production

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Abstract

Biofuel generation from local biomass resources can significantly contribute to greenhouse gas mitigation and cleaner energy production. In this regard, a hybrid Multi-Criteria Decision-Making (MCDM) approach was employed to prioritize appropriate biomass resources for biofuel production. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Additive Ratio Assessment (ARAS), and Weighted Aggregates Sum Product Assessment (WASPAS) were the employed MCDM approaches. Subsequently, ranking aggregation methods, i.e., Borda, Copeland, and Rank Mean, were applied to integrate the rankings obtained from the MCDM approaches. Guilan province of Iran was selected as a case study based on its promising potential for biofuel production from first-, second-, and third-generation biofuel resources. Initially, through an in-depth review of the literature and the use of academic professors' expert opinions, ten criteria were selected as the evaluation indices of the study: 1) creating technical side jobs, 2) preserving non-renewable energy resources, 3) relative advantage of biofuel production, 4) complexity of biofuel production process, 5) cost of the biomass conversion process, 6) biomass reusability, 7) cost of biomass supply, 8) environmental impacts of biomass accumulation, 9) adaptability of the biofuel production process to the size of biomass production units and the attitude and knowledge of the producers, and 10) energy self-sufficiency of the biomass producer. Moreover, the 11 investigated potential sources of biofuel production were rice, peanut, livestock and poultry wastes, rice waste, peanut waste, tea residues and its processing wastes, olive residues and its processing wastes, livestock and poultry slaughter and farm-raised fish wastes, municipal solid waste and sewage, forest and wood farming wastes, algae and *Azolla*. The results indicated that "municipal solid wastes and sewage", "forest and wood farming wastes" and "livestock and

poultry wastes” from the second-generation biofuels were identified as the most important biomass resources in the studied area.

Keywords: Biomass, Biofuel, Renewable, Waste to energy.

Introduction

Access to energy has a decisive role in the economic and social development of all societies ([Alfa et al., 2014](#)). Biofuel, as sustainable energy derived from a biomass resource, does not emit as much greenhouse gases (GHGs) as fossil-based fuels, is not a threat to food security, and does not jeopardize biodiversity ([Twidell & Weir, 2015](#)). Biomass is a sustainable and environmentally-friendly renewable energy resource with a remarkable potential to replace fossil fuel energy sources ([Biswas and Das, 2018](#)). In fact, the energy equivalent of available resources of biomass in the world is about eight folds greater than the current energy need on our planet ([Akay et al., 2005](#)).

Biomass resources are classified into three major categories, i.e., first-, second-, and third-generation ([Saratale et al., 2019](#)), based on the feedstocks and conversion technology applied for their generation ([Saladini et al., 2016](#)). First-generation biofuels are sourced from crop-based plants, which can also be considered as food, like biodiesel generation from peanut ([Ramos et al., 2019](#)). Second-generation biofuels are sourced from food, agricultural and forest, and municipal solid wastes ([Havlík et al., 2011](#)). The main issue about using first-generation biofuel resources is that there is a competition between energy generation and food production for arable land use ([Bajpai, 2019](#)). First-generation biofuels may also contribute to increasing the net GHG emissions of the energy production systems as a consequence of deforestation and chemical-based input consumption like chemical fertilizer ([Hanssen et al., 2019](#)). On the other hand, the disadvantages of second-generation biofuels are their high costs and several technical issues ([Mathimani and Pugazhendhi, 2019](#)).

Third-generation biofuels refer to energy production from algae and seaweed ([Ghadiryanfar et al., 2016](#)). The biofuels generated in this way mainly include the generation of biodiesel, bioethanol, and biohydrogen from green algae ([Dalena et al., 2019](#)). The biodiesel generation potential from microalgae is reportedly 15-300 times higher than that from traditional crops on land-use basis; moreover, microalga have a short harvesting cycle ([Alam et al., 2012](#)). However, biofuel generation from the third-generation biofuel resources (algal biomass) faces some difficulties like

high water requirement on industrial scale, some technical challenges like lipid extraction, dewatering, and geographical-based problems in some areas where the temperature is below the freezing point for a considerable period of the year (Lee and Lavoie, 2013).

In this regard, the Iran situation is an interesting case, as this country was reported as the country with the most massive GHG emissions in the Middle East. However, it has remarkable potential biomass resources to set up renewable-based energy systems (Zareei, 2019; Panahi et al., 2019). Biofuel generation from local biomass resources can significantly contribute to GHG mitigation and generation of clean energy. In this regard, the northern parts of Iran, which are also known as agricultural centers of the country, have a great potential for biomass energy generation. A study evaluated the potential of second-generation biofuel resources (cow manure, municipal solid wastes, peanut wastes, poultry manure, and rice wastes) in Guilan province, northern Iran. They reported that the total energy production potential from the investigated feedstock was about 77,000,000 GJ year⁻¹ and the results highlighted a promising potential of the second-generation biofuel resources in the region (Nikkhah et al., 2019). This province borders on the Caspian Sea, and it produces some crops that can be directly used for energy generation such as rice and peanut. Thus, it is highly essential to prioritize biomass resources in terms of energy generation in this region. Various methods may be applied to determine the appropriate biomass resources for biofuel production. However, the traditional single-criterion decision-making methods are no longer able to handle these complex problems (San Cristóbal, 2011), and thus, prioritizing the local biomass resources options for biofuel production must be addressed in a multi-criteria context. In this respect, multi-criteria decision-making (MCDM) – one of the dominant advanced and practical methodologies for comparison – can be applied to rank various biomass resources in terms of biofuel production. Several MCDM approaches have been developed for solving a complex problem in the renewable energy sector (Scott et al., 2012; Cobuloglu and Büyüktaktın, 2015; Sitorus and Brito-Parada, 2020). Each MCDM approach has its cons and pros, and the performance could be improved through the hybrid application of two or more approaches (Sakthivel and Ilankumaran, 2015). Therefore, the present study aimed to prioritize appropriate biomass resources for biofuel production by integrating some MCDM approaches in Guilan province, Iran.

2. Material and Methods

2.1. Survey area

As a potent agricultural and forestry area, northern Iran has a promising potential for biofuel production from first-, second-, and third-generation biofuel resources. Thus, Guilan province was selected as the case study for this research. This province covers an area of 14,042 km² between the latitudes 36°43' and 38°27' N. and the longitudes 48°53' and 50°34' E. Guilan province has massive sources of biomass, and a high crop and livestock diversity (including, tea, olive, peanut, rice, cattle, sheep, and aquatic animal) (Kouchaki-Penchah et al., 2017; Firouzi et al., 2017; Janbakhsh et al., 2018; Bakhshipour et al., 2020). Also, it is the second-largest rice-producing region in Iran (Shafieyan et al., 2017).

2.2. Criteria and alternatives

The present research was a descriptive research method in which data were collected with a questionnaire. To solve multi-criteria decision-making (MCDM) questions, criteria to measure the alternatives are needed. The questionnaire was designed after an in-depth review of the relevant literature and consulting with academic professors in Guilan province. It contained ten criteria or decision indices: 1) creating technical side jobs, 2) preserving non-renewable energy resources, 3) relative advantage of biofuel production versus the other biomass resources and other application, 4) complexity of biofuel production process, 5) cost of biomass conversion process, 6) biomass reusability, 7) cost of biomass supply, 8) environmental impacts of biomass accumulation, 9) adaptability of the biofuel production process to the size of biomass production units and the attitude and knowledge of the producers, 10) and energy self-sufficiency of the biomass producer. Eleven groups of biomass resources were considered in the study based on the available biomass resources in the studied region: 1) rice, 2) peanut, 3) livestock and poultry wastes, 4) rice waste, 5) peanut waste, 6) tea residues and its processing wastes, 7) olive residues and its processing wastes, 8) livestock and poultry slaughter, and farm-raised fish wastes, 9) municipal solid waste and sewage, 10) forest and wood farming wastes, 11) and algae and *Azolla-seaweed*. Among the biomass resources considered in this study, rice and peanuts fall into the feedstock category for first-generation biofuels. A Snowball technique was done to identify/recruit the ten experts. To provide respondents with a clear image of the criteria, authors provided an in-detailed explanation of each criteria and its sub-criteria. The respondents were asked to score the applicability of these

alternatives based on the ten criteria mentioned above on a 10-point scale (from 0 = inapplicable to 9 = very highly applicable).

2.3. Shannon Entropy method

Generally, in MCDM problems, it is needed to normalize the data through determining the relative importance of the criteria. The obtained normalized data (relative importance) are used to calculate the preference of a criterion against the other criteria in a decision-making procedure (Ghafari et al., 202). Shannon's entropy concept (Shannon, 1948) features a significant role in scientific theory (Ghorbani et al., 2012a). It has been applied in various scientific-based research areas, such as physics, social sciences, etc (Ghorbani et al., 2012b). Shannon entropy method estimates the importance of alternatives in four phases: i) decision-making matrix conversion into a dimensionless matrix (Eq. 1 and 2), ii) computing entropy index of the indicators (Eq. 3), iii) computing the degree of diversification (Eq. 4), and IV) determining the weight of the indices (Eq. 5).

$$R_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^m X_{ij}^2}} \quad (1)$$

$$P_{ij} = \frac{R_{ij}}{\sum_{i=1}^m R_{ij}} \quad (2)$$

$$E = -K \sum_{i=1}^m [P_i \times \ln P_i] \quad (3)$$

in which K is the entropy constant which is considered to be equal to $\frac{1}{\ln(m)}$

$$d_j = 1 - E_j \quad (4)$$

$$W_j = \frac{d_j}{\sum_{i=1}^n d_j} \quad (5)$$

2.4. TOPSIS

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) comprises a comparison between weighted reference solutions including a positive ideal solution and the negative ideal solution (Rudnik, 2017). To calculate the total importance of alternatives, it is

needed to compute their distances from the positive and the negative ideal solution simultaneously (Dočkalíková and Floková, 2018).

The phases for doing a TOPSIS study are: i) compute the weighted normalized decision matrix $V = (V_{mn})_{M \times N}$ using Eq 6, ii) determine the positive ideal solution S^+ using Eq 7, iii) estimate the negative ideal solution \bar{S} using Eq 8, IV) compute the distances of each alternative from the positive ideal solution S^+ and the same for the negative ideal solution \bar{S} (Drissi, and Oumsis, 2015; Liang and Meng, 2019).

$$V_{mn} = w_n \cdot r_{mn} \quad (w_n, n=1, \dots, N) \quad (6)$$

$$S^+ = \left(V_1^+, V_2^+, \dots, V_N^+ \right) = \{ (\max_m V_{mn} / n \in C_{ben}), (\min_m V_{mn} / n \in C_{cost}) \}, \quad (7)$$

where C_{ben} refers to the set of benefit criteria and C_{cost} is the set of cost criteria.

$$\bar{S} = \left(\bar{V}_1, \bar{V}_2, \dots, \bar{V}_N \right) = \{ (\min_m V_{mn} / n \in C_{ben}), (\max_m V_{mn} / n \in C_{cost}) \}, \quad (8)$$

2.5. ARAS method

Based on the Additive Ratio Assessment (ARAS) method, a utility function value estimates the complex relative efficiency of a feasible alternative, which is directly proportional to the relative effect of the values and weights of the key criteria considered in a study (Streimikienė et al., 2016). In this study, the ARAS method was used and followed by the protocols suggested by Zavadskas et al. (2010) and Streimikiene et al. (2016) as following:

Phase 1: firstly, the decision-making matrix (DMM) should be formed. Any problem in the MCDM of a discrete optimization problem can be defined by the following matrix (Medineckiene et al., 2015):

$$X = \begin{bmatrix} x_{01} & x_{0j} & \dots & x_{013} \\ x_{i1} & x_{ij} & \dots & x_{i13} \\ \dots & \dots & \dots & \dots \\ x_{51} & x_{5j} & \dots & x_{513} \end{bmatrix} \quad (9)$$

$$i = 0, 1, \dots, 5$$

$$j = 1, \dots, 13$$

where i refers to the number of alternatives, j is the number of criteria describing each alternative, x_{513} is the value showing the performance of the i th alternative with reference to the j th criterion, and x_{0j} is the optimal value of the j th criterion. In the case if the optimal value of the j th criterion is unknown, then the following equation can be applied:

$$x_{0j} = \max_i x_{i13}, \text{ if } \max_i x_{i13} \text{ is preferable} \quad (10)$$

$$x_{0j} = \min_i^* x_{i13}, \text{ if } \min_i^* x_{i13} \text{ is preferable} \quad (11)$$

Basically, the performance values x_{ij} and the criteria weights w_j are considered as the entries of a matrix. The system of criteria and the values and initial weights of criteria are calculated through the inputs of the experts' opinions. The information may then be revised by the interested parties considering their aims, challenges and potential opportunities (Zavadskas and Turskis, 2010).

In the next phase, the alternatives are prioritized in several phases. Normally, the criteria have different dimensions in an MCDM problem. The next phase aims to obtain dimensionless weighted values from the comparative criteria. In this study, the ratio to the optimal value was employed in order to avoid the problem caused by dimension differences between the criteria (Streimikienė et al., 2016). The ratio to the optimal value has been described by several theories (Zavadskas et al., 2012; Sheikh and Ameri, 2013). It can be expressed as the two intervals of $[0; 1]$ or the interval $[0; \infty]$ through employing the normalization of a DMM (Turskis et al., 2013).

Phase 2: the initial values of all criteria are being normalized (describing values $\overline{x_{ij}}$ of normalized decision-making matrix \overline{X}) (Medineckiene et al., 2015).

$$\bar{X} = \begin{bmatrix} - & - & - \\ x_{01} & x_{0j} & x_{013} \\ - & - & \dots \\ x_{i1} & x_{ij} & \dots x_{i13} \\ \dots & \dots & \dots \\ - & - & \dots \\ x_{51} & x_{5j} & x_{513} \end{bmatrix} \quad (12)$$

i= 0, 1,... ,5

j= 1, ..., 13

The criteria, whose preferable amounts are maxima, are normalized using Eq. 13 (Streimikienė et al., 2016):

$$x_{513} = \frac{x_{513}}{\sum_{i=0}^5 x_{513}} \quad (13)$$

The criteria, whose preferable values are minima, were normalized using Eq 14 and 15:

$$x_{513} = \frac{1}{x_{513}} \quad (14)$$

$$x_{513} = \frac{x_{513}}{\sum_{i=0}^5 x_{513}} \quad (15)$$

Phase 3: this phase defines the normalized-weighted matrix \hat{X} (Stević et al., 2016). The criteria can be expressed with weights $0 < w_j < 1$. It should be noted that only well-founded weights can be applied since weights are always subjective and impact the solution. The expert evaluation method is usually used to calculate the amounts of the weight w_j . The sum of weights w_j would be limited as follows:

$$\sum_{j=1}^{13} w_j = 1 \quad (16)$$

$$\hat{X} = \begin{bmatrix} \hat{x}_{01} & \hat{x}_{0j} & \hat{x}_{013} \\ \hat{x}_{i1} & \hat{x}_{ij} & \hat{x}_{i13} \\ \vdots & \vdots & \vdots \\ \hat{x}_{51} & \hat{x}_{5j} & \hat{x}_{513} \end{bmatrix} \quad (17)$$

$$i = 0, 1, \dots, 5$$

$$j = 1, \dots, 13$$

The normalized-weighted values of all the criteria can be expressed as the following equation:

$$\hat{x}_{513} = \bar{x}_{513} w_j, \quad i = 0, \dots, 5 \quad (18)$$

where w_j is the weight or in other words the importance of the j th criterion and \bar{x}_{513} is the normalized rating of the j th criterion. Eq. (19) calculates the values of optimality function:

$$S_i = \sum_{j=1}^{13} \hat{x}_{513}, \quad i = 0, \dots, 5 \quad (19)$$

where S_i refers to the value of the optimality function of the i th alternative.

The larger amount of the value means it is better and the smallest one shows it is the worst. Taking the calculation process into consideration, the optimality function S_i features a direct and proportional relationship with the values X_{ij} and weights W_j of the investigated criteria and their relative influence on the ultimate result. Thus, the larger the value of the optimality function S_i is, the more effective the choice will be. The priorities of alternatives are often specified based on the worth S_i . The degree of the alternative utility is decided by a comparison of the variant, which is analyzed, with the ideally best one S_0 . The applied equation to calculate the utility degree K_i of an alternate a_i is given below:

$$K_i = \frac{S_i}{S_0}, \quad i = 0, \dots, 5 \quad (20)$$

where S_i and S_0 are the optimality criterion values which can be calculated using Eq. (19). The obtained K_i values are in the interval $[0, 1]$ and can be ranked in an increasing sequence based on the recommended order of precedence. The complex relative efficiency of the feasible alternative can be identified based on the utility function values (Varmazyar et al., 2016).

2.6. WASPAS method

This study followed the proposed procedure for the WASPAS method according to the study of [Rudnik \(2017\)](#) as following:

Phase 1: determine the normalized decision matrix $R = (r_{mn})_{M \times N}$ through the following equations (Su et al., 2017):

$$r_{mn} = \frac{x_{mn}}{\max_n x_{mn}} \quad \text{if } n \in C_{ben} \quad (21)$$

$$r_{mn} = 1 - \frac{x_{mn}}{\max_n x_{mn}} \quad \text{if } n \in C_{cost} \quad (22)$$

where C_{ben} is the set of benefit criteria and C_{cost} is the set of cost criteria. For the benefit criterion, the highest value of alternative evaluation is preferred whereas for the cost criterion, it is the opposite and the lowest value is desired.

Phase 2: The weighted normalized decision matrix $V = (v_{mn})_{M \times N}$ determination using the weight values $(W_n, n=1, \dots, N)$ as follows:

$$V_{mn} = W_n \cdot r_{mn} \quad (23)$$

Phase 3: aggregate the total relative importance of the m th alternative using Eq. 24:

$$Q_m = \sum_{n=1}^N v_{mn} \quad (24)$$

The WASPAS method is an approach combining weighted sum and weighted product models (WSM and WPM). A study claimed that the WASPAS method is more accurate than the use of only WPM or WSM ([Zavadskas et al., 2012](#)).

Phase 4: determine the weighted sum model (WSM): aggregate the total relative importance of the n th alternative by Eq. (25):

$$Q_n^{(1)} = \sum_{m=1}^M W_n \cdot r_{mn} \quad (25)$$

where r_{mn} is calculated by using Eq. (21) and (22).

Phase 5: specify the weighted product model (WPM) for which aggregate the total relative importance of the n th alternative as follows:

$$Q_n^{(2)} = \prod_{n=1}^N (v_{mn})^{W_n} \quad (26)$$

Phase 6. Calculate the total importance of the n th alternative by the following equations (Zavadskas et al., 2012; Rudnik, 2017; Turskis et al., 2015)

$$Q_n = \lambda \cdot Q_n^{(1)} + (1 - \lambda) \cdot Q_n^{(2)}, \lambda \in [0,1], \quad (27)$$

where

$$\lambda = \frac{\sum_{n=1}^M Q_n^{(2)}}{\sum_{n=1}^M Q_n^{(1)} + \sum_{n=1}^M Q_n^{(2)}} \quad (28)$$

2.7. Final ranking of alternative by the integrated methods

Decision- making process may not be limited to only a single method and various methods can be integrated to achieve a better result and therefore, techniques have already been suggested to integrate the rankings obtained from various methods, such as Borda's count, Copeland's, and ranks averaging method (Ghafari et al, 2020).

Borda's count: In this method, a non-diagonal $M \times M$ matrix is formed in which the description of the i th row to the j th column ($i \neq j$) is specified in terms of the number of wins. If the number of the wins in techniques is more, it is coded with M in which the row is preferred to the column, but if the column is preferred to the row or the number of wins is equal, it is coded with X. Finally, the sum of wins in each row (M 's) bases the ranking. The more the number of wins is, the higher the rank will be.

Copeland's method: This method calculates not only the wins but also the number of losses for each alternative. In this method, M in row i means win but in column j means loss. The basis for ranking is the difference in the number of M's in column j ; that is, the difference in wins and losses will base the ranking.

$$Ti = \sum C_i - \sum XR_j \quad (29)$$

Ranks Mean: This is the easiest way to calculate the mathematical average of the ranks derived from the ARAS, WASPAS, and TOPSIS methods to be used for the final decision-making. The alternative with the lowest average is positioned at the top rank (Banihabib et al., 2017).

Finally, the ranks were aggregated to calculate the final rank of the alternatives. The alternative with lower rank was prioritized higher. Figure 1 shows the workflow of the research method from choosing alternatives and criteria to final ranking of biomass resources.

The limitation of this study comes from its limited number of available experts on different generation of biofuel production systems in the studied region. Another limitation of this study was that only a limited number of criteria was considered to avoid taking the experts' time and energy to think about the less important criteria.

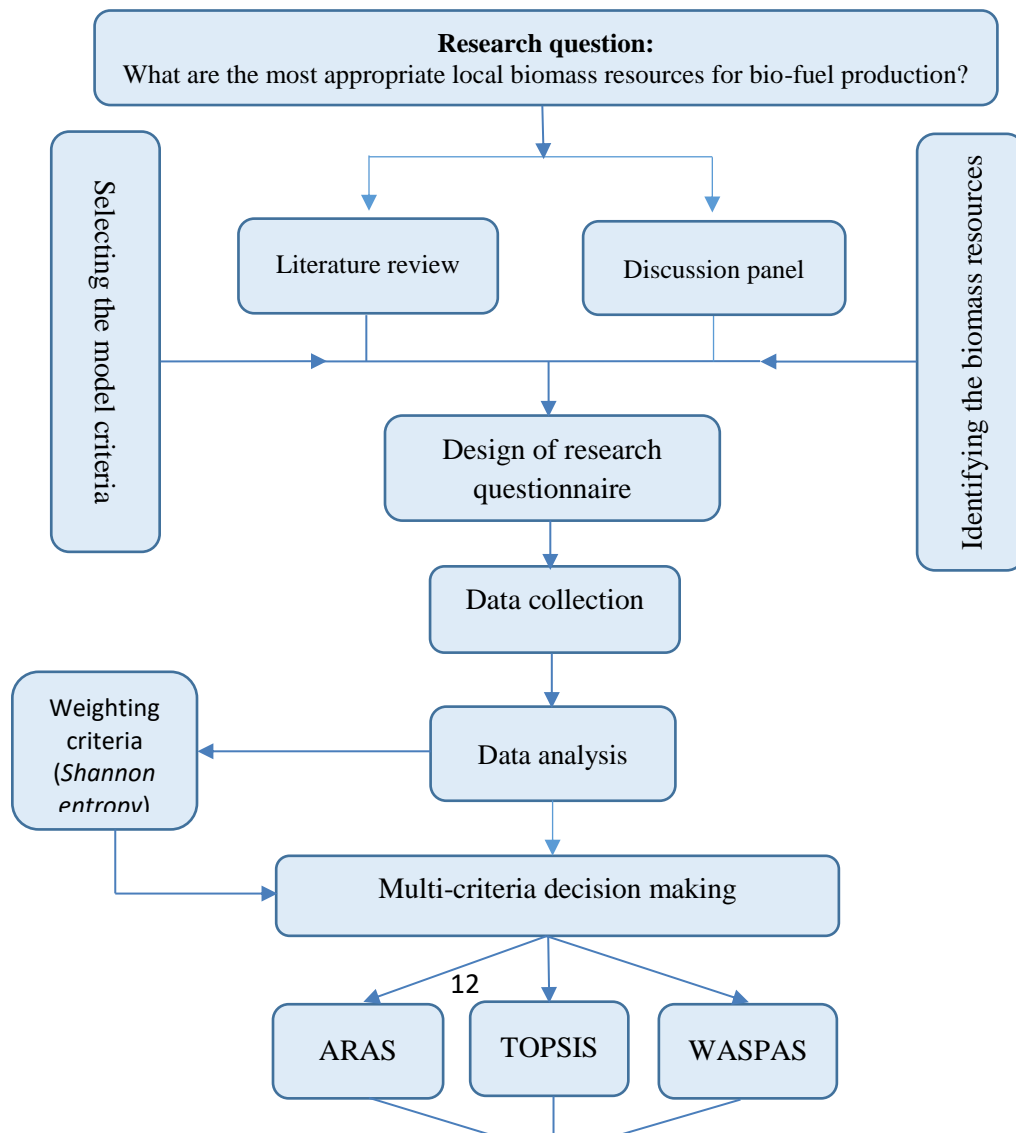


Fig 1. Hybrid MCDM to prioritize biomass resources' options

3. Results and Discussion

3.1. Shannon entropy results

Table 1 shows the weights of the indices used to prioritize biomass resources using the Shannon entropy method. Accordingly, the three indices of “relative advantages of biofuel production over other biomass applications”, “conservation of non-renewable energy resources”, and “energy self-sufficiency of the biomass producer” were identified as the most important indices to select suitable biomass resources.

First-generation biofuels, including bioethanol and biodiesel, are generated from biomasses that can often be used as human food (Alalwan et al., 2019). They may help mitigate GHG emissions, but the land used to produce their feedstock can be challenging (Fivga et al., 2019). Moreover, biofuel generation from edible feedstock can be problematic in the current situation of the world's food shortage (Alam et al., 2012). Therefore, choosing “the relative advantages of biofuel production over other biomass applications” as the first index to classify the biomass resources may be justifiable.

Today, the world still strongly depends on the limited resources of non-renewable fossil fuels (Ansari et al., 2011; Xu et al., 2018). Therefore, supplying a part of the fuel requirement from biomass resources can be vital to postpone the exhaustion of the world's oil reserves (Akyürek, and Turgut, 2019). Hence, it is quite reasonable that “conservation of non-renewable energy resources” was ranked as the second most important index to prioritize the biomass resources in our study.

“Energy self-efficiency of the biomass producer” was identified as the third most important index to evaluate the preference of biomass as the biofuel feedstock. It expresses to what extent the bioenergy generated from biomass can supply the energy requirement of the biomass producer unit. For instance, suppose rice husk, as a major byproduct of a rice milling process, is used as a feedstock to meet the energy demand of the rice mill. This is an advantage over the other biomasses in the view of energy self-efficiency of the rice mill as both the biomass producer and bioenergy consumer, because biomass transportation costs can be saved in the process of bioenergy generation. Rice husk is a source of bioenergy because of its organic content (Yaghoubi et al., 2019). It can provide electricity through gasification for small-scale power generators or thermal energy needed for paddy drying or parboiling process in rice mills (Kumar et al., 2013; Roy et al.,

2006). The weight values which are shown in Table 1, along with the values of the indices were used as inputs for the TOPSIS, ARAS, and WASPAS methods.

Table 1. Weights of the indices used to prioritize biomass resources using the Shannon entropy method

Indices	Rank	Weight
The relative advantage of biofuel production over other biomass applications	1	0.127
Conservation of non-renewable energy resources	2	0.125
Energy self-sufficiency of biomass producer	3	0.123
Creating technical side jobs	4	0.121
Adaptation to the size of bio-energy consumer units and the producer's attitude and knowledge	5	0.120
Reusability of biomass material	6	0.116
Environmental impacts of biomass accumulation	7	0.108
Cost of biomass supply	8	0.092
Costs of biomass conversion to biofuel	9	0.065
The complexity of the process of converting biomass into biofuel	10	0.003
Total		1

3.2. TOPSIS, ARAS and WASPAS results

According to the TOPSIS analysis, “forest and wood farming wastes” ($C=0.727$), “livestock and poultry wastes” ($C=0.642$), and “municipal solid waste and sewage” ($C=0.632$) were identified as the most important biomass resources to generate bio-energy. The results in Table 2 indicate that the second-generation biomass resource options are superior to the third and first-generation ones. Peanuts and rice were ranked last in the ranking as representatives of the first-generation biomass resources.

After processing the decision matrix using ARAS by Eq. (9)-(20) and WASPAS by Eq. (21)-(28) arranging the alternatives according to the Q and K values in descending order, the biomass resources were prioritized as demonstrated in Table 2. Based on the results of these two methods, as opposed to the TOPSIS technique, two biomass resources of municipal solid waste and sewage were identified as the priority of biofuel generation feedstock. In the WASPAS technique, two sources of “livestock and poultry wastes” and “forest and wood farming wastes” were ranked second and third, but according to the results of the ARAS analysis, “forest and wood farming wastes” and “livestock and poultry wastes” were ranked second and third, respectively.

Table 2. Prioritization of the biomass resources using the TOPSIS, ARAS and WASPAS methods

Biomass resources	TOPSIS		WASPAS		ARAS		Generation class
	C	Rank	Q	Rank	K	Rank	
Municipal solid wastes and sewage	0.632	3	0.905	1	0.899	1	2nd
Livestock and poultry wastes	0.642	2	0.860	2	0.852	3	2nd
Forest and wood farming wastes	0.727	1	0.860	3	0.857	2	2nd

Livestock and poultry slaughter, farmed-raise fish wastes	0.632	4	0.843	4	0.836	4	2nd
Rice waste	0.628	5	0.814	5	0.808	5	2nd
Peanut waste	0.554	6	0.776	6	0.771	6	2nd
Algae and Azolla	0.550	7	0.617	7	0.758	7	3rd
Olive cultivation and its processing wastes	0.523	8	0.748	8	0.743	8	2nd
Tea cultivation and Its processing wastes	0.511	9	0.742	9	0.736	9	2nd
Rice	0.368	10	0.617	10	0.615	10	1st
Peanut	0.361	11	0.606	11	0.604	11	1st

Due to the differences in the results of the TOPSIS, ARAS and WASPAS methods, the results of these techniques were merged, using the Borda count, Copeland's, and Rank Mean methods for the final ranking of options. Table 3 shows the procedure of the Borda, Copeland's, and Rank Mean methods to set the priority of alternatives. Accordingly, in the final step, "municipal solid wastes and sewage" was determined to be the most important biomass resource to produce bioenergy in Guilan Province, northern Iran (Table 4).

Around 2.5 million people live in the 16 counties of Guilan province, consuming vast quantities of goods daily and generating an excessive amount of 2,200 tons of municipal solid wastes. Of this, up to 700 tons of waste is produced in Rasht, the capital of the province, and is mostly dumped in Saravan Landfill, the largest landfill in northern Iran ([Shariatmadari et al., 2018](#); [Nikkhah et al., 2019](#)). Due to the proximity of Guilan's landfills to the adjacent forests and regional rivers, it is a severe environmental threat to the soil and water resources and the Caspian Sea. Moreover, methane emission from landfills contributes to global warming ([Nikkhah et al., 2018](#)). About 84 percent of Iran's urban wastes are piled in open landfills, while only about 10 percent is used to produce compost and about 6 percent is recycled ([Mir and Nabavi, 2015](#)). Since most municipal waste is organic ([Hoornweg and Bhada-Tata, 2012](#)), the use of the environmentally dangerous municipal waste and its hazardous leachate to generate bioenergy is an excellent opportunity to improve the environment and it will also bring significant economic benefits to Guilan Province. It was estimated that there is a potential of about 648,000 MJ/day of bioenergy production through biogas generation from the municipal waste of Guilan province. The potential of electricity generation has also been rated to be about 156,000 MWh/day ([Nikkhah et al., 2019](#)). Referring to the municipal solid waste production in Turkey as a main concern of the country, [Melikoglu \(2013\)](#) emphasized the significant economic and environmental benefits of electricity and biogas generation from it. Their estimates showed that about 8,500 GWh of electricity or 3,100 million

m³ of methane could have been produced from municipal solid wastes of Turkey's landfills in 2012.

Table 3. The matrix of the results of the TOPSIS, ARAS and WASPAS methods in selecting the most important biomass resources in Guilan province, Iran

Biomass resources	1	2	3	4	5	6	7	8	9	10	11	$\sum C$	R	$\sum C - \sum R$
Rice	-	M	X	X	X	X	X	X	X	X	X	1	10	-8
Peanut	X	-	X	X	X	X	X	X	X	X	X	0	11	-10
Rice wastes	M	M	-	M	M	M	X	X	X	X	M	6	5	2
Peanut wastes	M	M	X	-	M	M	X	X	X	X	M	5	6	0
Olive cultivation and its processing wastes	M	M	X	X	-	M	X	X	X	X	X	3	8	-4
Tea cultivation and its processing wastes	M	M	X	X	X	-	X	X	X	X	X	2	9	-6
Livestock and poultry wastes	M	M	M	M	M	M	-	M	X	X	M	8	3	6
Livestock and poultry slaughter, and farm-raised fish wastes	M	M	M	M	M	M	X	-	X	X	M	7	4	4
Forest and wood farming wastes	M	M	M	M	M	M	M	M	-	X	M	9	2	8
Municipal solid wastes and sewage	M	M	M	M	M	M	M	M	M	-	M	10	1	10
Algae and Azolla	M	M	X	X	M	M	X	X	X	X	-	4	7	-2
$\sum R$	9	10	4	5	7	8	2	3	1	0	6			

Number of M in each row= $\sum C$, Number of M in each column= $\sum R$

Table 4. The results of the TOPSIS, ARAS, and WASPAS outputs in selecting the most important biomass resources in Guilan province, Iran

Biomass resources	Copeland	Borda	Rank Mean	Mean of methods	Final rank
Municipal solid wastes and sewage	1	1	1	1	1
Forest and wood farming wastes	2	2	2	2	2
Livestock and poultry wastes	3	3	3	3	3
Livestock, poultry slaughter, and farm-raised fish wastes	4	4	4	4	4
Rice wastes	5	5	5	5	5
Peanut wastes	6	6	6	6	6
Algae and Azolla	7	7	7	7	7
Olive cultivation and its processing wastes	8	8	8	8	8
Tea cultivation and its processing wastes	9	9	9	9	9
Rice	10	10	10	10	10
Peanut	11	11	11	11	11

The results in Table 4 also indicate that “forest and wood farming wastes” was identified as the second most important biomass resource to generate bioenergy in the studied area.

Approximations show that forestry biomass may be a major source of bioenergy production globally, while the necessary woody biomass may be provided without risking the source of the wood industry and without more threat to the survival of forests (Ladanai and Vinterbäck, 2009; Paulo et al., 2015)

The yearly woody biomass production of the world is reported to be about 4.6 Gt, of which 60 percent is used as bioenergy resource, 20 percent as industrial wood, and the rest is lost in forests or timber farms. A cubic meter of forest waste remains in the field for each cubic meter of material harvested (Tripathi et al., 2019). The forest area of Guilan province is currently reported to be around 565,000 ha (Anonymous, 2020). A huge amount of old dead dry trees and branches fell on the forest floor can be used as a reliable source of woody biomass without endangering the forest survival. Furthermore, Guilan province has good potential for timber farming to meet the domestic need. It is also reported that the area of poplar cultivation in Guilan province is currently 300,000 ha (Anonymous, 2020). The woody residues remained after harvesting the poplar trees in the timber farms, and the wood processing remnants, including bark, slabs, and sawdust in woodworking workshops may also be used as a good source of wood biomass in the studied region. The heating value of poplar wood was reported to be at least 18.19 MJ kg⁻¹ (Gonçalves et al., 2018).

Finally, the results indicated that “livestock and poultry manures” is the third most preferred biomass in the studied area (Table 4). Poultry manure has a promising potential for biogas generation as a beneficial alternative of this agro-industry to overcome its adverse environmental effects (Calhan et al., 2016; Dornelas et al., 2018). The biogas conversion factor for poultry manure is around 0.8 m³ kg⁻¹ of the destroyed volatile solid content of manure. Accordingly, the potential biogas generated from chicken manure in Guilan province was estimated to be about 17 and 14 million m³ in 2010 and 2011 respectively, and the potential of electricity generation was estimated to be around 102,000 and 84,000 MWh respectively. The potential biogas and electricity generation from cow manure was also rated at 9.4 million m³ and 548 GWh, respectively (Nikkhah et al., 2019).

The results of this study highlighted that according to the experts' opinions, the second-generation biofuel resources are among the top priorities for energy production in the studied region. Life cycle assessment of first-generation biofuels shows little to no benefit in terms of GHG mitigation compared to petroleum fuels. Second-generation biofuels however are more

efficient in the point of GHG mitigation and avoiding other sustainability challenges, such as land use (Kendall and Yuan, 2013).

4. Conclusion

Biofuel generation from local biomass resources can contribute towards moving to a sustainable energy generation system. Thus, it is highly important to choose an appropriate biomass resource, based on the availability of biomass and taking into account multiple criteria together. In this respect, multi-criteria decision-making (MCDM) could be used to handle this complex problem, given that the traditional single-criterion decision-making methods are no longer able to handle it. Moreover, each MCDM approach has its pros and cons and thus the hybrid application of MCDM approaches could improve the performance of the decision-making process. Therefore, this study suggests a hybrid MCDM approach to select appropriate biomass resources for biofuel production that demands taking into account multiple criteria together, which can be used at the macro (country-based) and micro (local-based) scales. For this purpose, three MCDM approaches, i.e., TOPSIS, ARAS and WASPAS were applied and then ranking aggregation methods, including, Borda's count, Copeland's, and Rank Mean were used to integrate the final rank of alternatives. The case study was Guilan province of Iran. Ten criteria and 11 alternatives were considered in this research. The results indicated that some second-generation biomass resources, such as municipal solid wastes and sewage", "forest and wood farming wastes" and "livestock and poultry wastes" are appropriate to be used as feedstocks for biofuel production in the investigated region. Further research is needed to look at techno-economic aspects of biofuel production from feedstocks recommended by this study.

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