Use of Multicriteria Decision Making (MCDM) Methods for Biomass Selection Aimed to Fischer Tropsch Processes

Javier Martínez[#1], Ricardo A. Narváez C.[*2],

[1] *Instituto Nacional de Eficiencia Energética y Energías Renovables (INER),*
Adress: Quito, Ecuador. Tel +593 (0) 2 3931390 ext: 2079,

Abstract- *Proper determination of the physicochemical properties of a fuel is an important task to fulfil the requirements for a reactor. The number of biomass types able to act as fuel with different properties available to provide to a bioreactor is vast. However, application of efficiency and systematic mathematical approaches may achieve the evaluation to determine if a given type of feedstock will perform properly when it is desired to feed a reactor with it. Multi-criteria decision making methods (MCDM) consider characteristic properties and qualitative criteria to assign importance to each alternative in order to select the most suitable option. This research use MCDM for the selection of the fuel to be gasified in advance for a Fischer Tropsch reactor.*

The MCMD methods implemented are operational competitiveness rating analysis (OCRA) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) The criteria weighting was performed by compromised weighting method composed of AHP (analytic hierarchy process) and Entropy methods. The results illustrated that white grain appears as the best choice for a biomass fuel for the two MCMD.

Keywords- *Biomass, biofuel, multi-criteria decision making methods, MCDM,*

I. INTRODUCTION

Biomass is a natural treasure for chemicals that up to now are made from fossil resources. Unfortunately, the heterogeneity and complexity of biomass still preclude exploitation of its full potential. New technologies for economical valorisation of biomass are under development, but cannot yet compete with petrochemical processes. However, rising prices of fossil resources, inevitably will lead to replacement of oil refineries with other biorefineries or biomass-based processes.

The concern on impacts of global warming and decrease of the conventional fossil fuel sources enhance the interest to renewable energy sources. As a very versatile energy source, biomass can be used in transport, electricity and heating [1-2]

Biomass, sun (e.g. photovoltaic solar cells and solar heat collectors), wind (e.g. wind turbines), water (e.g. hydropower, tidal energy) and geothermal resources are all sources of renewable energy, but biomass is the only renewable resource of carbon for the production of chemicals, materials and fuels. Before the onset of the petrochemical era, renewable feedstock supplied a significant portion of the global chemical and energy needs [3-4]. However, a study regarding biomass selection forFischer Tropsch reactors is required in order to boost the propagation of this technology.

The term Biomass to Liquid BtL is applied to synthetic fuels made from biomass through a thermochemical route. The objective is to produce fuel components that are similar to those of current fossil-derived petrol (gasoline) and diesel fuels; hence they can be used in existing fuel distribution systems and with standard engines. They are also known as synfuels.

Biomass is pre-treated and then converted to synthesis gas (syngas) via gasification. The resulting syngas is then cleaned prior to conversion to liquid biofuels, typically via Fischer Tropsch or the Mobil Process outlined below.

Although the individual steps for production of BtL are well known (and have been demonstrated successfully at industrial scale), integrating the various technologies for commercial production of BtL has proved challenging.

The Fischer–Tropsch process is a collection of chemical reactions that converts a mixture of carbon monoxide and hydrogen into liquid hydrocarbons. It was first developed by Franz Fischer and Hans Tropsch in 1925. The process, a key component of gas to liquids technology, produces a synthetic lubrication oil and synthetic fuel, typically from coal, natural gas, or biomass

Multi criteria decision making methods (MCDM) appear as an alternative in engineering design due to its adaptability for different applications [5-6]. The MCDM methods can be broadly divided into two categories, as (i) multi-objective decision-making (MODM) and (ii) multi-attribute decision-making (MADM). There are also several methods in each of the above-mentioned categories. Priority-based, outranking, preferential ranking, distance-based and mixed methods are some of the popular MCDM methods as applied for evaluating and selecting the most suitable solution for diverse engineering applications. In most MCDM methods a certain weight is assigned to each criterion.

This paper solves the problem of defining biomass fuel characteristics using recent mathematical tools and techniques for accurate ranking of the alternatives by five preference ranking- based MCDM methods, i.e. (OCRA) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) methods have been implemented. The criteria weighting was performed by compromised weighting method composed of analytic hierarchy process (AHP) and Entropy methods. For these methods, a list of all the possible choices from the best to the worst suitable biofuel is obtained, taking into account different criteria.

II. MATERIALS AND METHODS

II. I. DEFINITION OF THE DECISION MAKING PROBLEM

Biomass can be characterized by the Moisture content, Content of volatiles, Content of ashes, Elemental composition, Bulk density, Energy density [7] The elementary composition determines the heating value. Moisture content ranges between 10 and 60% and also has a significant influence on the lower heating value (LHV). In general, it can be observed that biomass has inferior heating values compared to fossil fuels like black coal or crude oil.

The energy density with the SI-unit [J/m^3] is defined with the lower heating value and the bulk density [8]. The bulk density is the space that for example wood logs or straw bales fill per kilogram. Biomass normally has a low bulk density, and together with the low heating values, its energy density is relatively small. As a result, the transport costs for biomass are not competitive. It should therefore only be used in close proximity to its origin. This explains the decentralized character of energy generation from biomass: unlike fossil power plants, where high energy density fuel can be transported to central conversion plants with several megawatts up to a few gigawatts, the biomass to energy conversion takes place in small plants with power out-puts of 50 kW – 300 MW [9] In case of electricity as secondary energy, conduction losses can be reduced. Another way is to produce secondary energy carriers like ethanol, biodiesel or second generation biofuels with higher energy density and transport them to the place of consumption.

One of the most important biomass property is considered to be the lower heating value (LHV), the highest values of which are desired in order to provide the most quantity of energy to a determine application. In addition, lower values of [%] Moisture Content (MC) would be favourable. Furthermore, higher bulk densities (D) of the biomass can lead to a less volume of fuel. The lowest valuesof ash melting (AM) are necessary to eliminate the impurities. High Ash dry and volatile components are which leads to higher conversion rates. Among these six criteria, it is desired that moisture content and ash melting are as low as possible.Seven alternatives for the biomass fuel were taken into consideration: straw, wood, miscanthus, whole cereal, plants, cattle manure, rice husk, wheat grain. The properties of the biomass fuel alternatives are given in Table I and their average values were used.

Table 1. Material properties for a biomass fuel (1)-(12)

N.	Biomass feedstock	(LHV) LHV [MJ/kg]	(MC) Moisture Content [%]	(D) Bulk density (kg/m^3)	(AM) Ash melting [°C]	(AD) Ash, dry [%]	(VD) Volatiles, dry [%]
1	Straw	18,25	15	67,5	1040	5	78,0
2	Wood	19,25	40	320	1150	2,1	77,5
3	Miscanthus	18,5	20	160	1040	3,2	81,0
4	Whole cereal plants	18,25	15	60	1550	5	78,0
5	Cattle manure	16,4	14	550	1304,5	13,67	60,5
6	Rice Husk	13,5	3,5	100	1505	12,7	67,9
7	Wheat grain	16,66	7	790	1035	7,27	15,2

III. MULTI-CRITERIA DECISION MAKING METHODS

III.I CRITERIA WEIGHTING

The criteria weights are calculated using a compromised weighting method, where the AHP and Entropy methods, in order to take into account the subjective and objective weights of the criteria and to obtain more reasonable weight coefficients.

III.I. I. ANALYTIC HIERARCHY PROCESS (AHP)

The AHP method was developed by Saaty [10] to model subjective decision-making processes based on multiple criteria in a hierarchical system. The method composes of three principles:

a) Structure of the model.
b) Comparative judgment of the alternatives and the criteria.
c) Assessing consistency in results.

a) Structure of the model.

In order to identify the importance of every alternative in an application, each alternative has been assigned a value. The ranking is composed by three levels: 1). general objective, b). criteria for every alternative, c). alternatives to regard [10]

b) Comparative judgment of the alternatives and the criteria.

The weight of criteria related to other is set in this section. To quantify each coefficient it is required experience and knowledge of the application. Saaty [10] classified the importance parameters show in Table II. The relative importance of two criteria is rated using a scale with the digits 1, 3, 5, 7 and 9, where 1 denotes ''equally important'', 3 for ''slightly more important'', 5 for ''strongly more important'', 7 for ''demonstrably more important'' and 9 for ''absolutely more important''. The values 2, 4, 6 and 8 are applied to differentiate slightly differing judgements. The comparison among n criteria is presented in matrix A (nxn), the global arrange is expressed in equation (2).

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix} a_{ii} = 1, a_{ji} = \frac{1}{a_{ij}}, a_{ij} \neq 0 \quad (2)$$

Afterwards, from matrix A it is determined the relative priority among properties. The eigenvector w is the weight importance and it corresponds with the largest eigenvector (λ_{max}):

$$(A - \lambda_{max})w = 0 \quad (3)$$

The consistency of the results is represented by the pair wise comparison of alternatives. Matrix A can be ranked as 1 and λ_{max} = n [10]

c) Consistency assessment

In order to ensure the consistency of the subjective perception and the accuracy of the results it is necessary to distinguish the importance of alternatives among them. In equations (4) and (5) is shown the consistency indexes required to validate the results.

$$CI = \frac{(\lambda_{max} - n)}{n-1} \quad (4)$$

$$CR = \frac{CI}{RI} \quad (5)$$

Where:
n: Number of selection criteria.
RI: Random index.
CI: Consistency index.
CR: Consistency relationship.
$\lambda_{max}(A)$: Largest eigenvalue.

The CR should be under 0.1 for a reliable result otherwise, the importance coefficient (1-9) has to be set again and CR recalculated(16). The RI is determined for different size matrixes, and its value is 1.32 for an 7x6 matrix.

III. I. II. ENTROPY METHOD

Entropy method indicates that a broad distribution represents more uncertainty than that of a sharply peaked one [5]. Equation (6) shows the decision matrix A of multi-criteria problem with m alternatives and n criteria:

$$A = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \ddots & x_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nn} \end{bmatrix}; x_1, x_2, \dots x_n \quad (6)$$

Where $x_{ij}(i = 1, 2, \dots, m;\ j = 1, 2, \dots, n)$ is the performance value of the ith alternative to the jth criteria.

The normalized decision matrix P_{ij} is calculated by equation (7), in order to determine the weights by the Entropy method.

$$P_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (7)$$

The Entropy value E_j of jth criteria can be obtained as:

$$E_j = -k \sum_{i=1}^{m} P_{ij} \ln(P_{ij}) \quad j = 1,2, \dots, n \quad (8)$$

Where $k = \frac{1}{\ln m}$ is a constant that guarantees $0 \leq Ej \leq 1$ and m is the number of alternatives. The degree of divergence (d_j) of the average information contained by each criterion can be obtained from Eq. (9):

$$d_j = \left|1 - E_j\right| \tag{9}$$

Thus, the weight of Entropy of jth criteria can be defined as:

$$\beta_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{10}$$

III. I. III. OCRA METHOD

The OCRA method was developed to measure the relative performance of a set of production units, where resources are consumed to create value-added outputs. OCRA uses an intuitive method for incorporating the decision maker's preferences about the relative importance of the criteria. The general OCRA procedure is described as below [12]:

Step 1: Compute the preference ratings relating them with the non- beneficial criteria. The aggregate performance of ith alternative related to all the input criteria is calculated using the following equation:

$$\bar{I}_i = \sum_{j=1}^{n} w_j \frac{\max\left(x_j^m\right) - x_j^i}{\min\left(x_j^m\right)}$$

(i=1,2,…,m, j=1,2,…,n) (11)

Where $\bar{I}_i$ is the measure of the relative performance of ith alternative and x_j^i is the performance score of ith alternative regardingthen jth input criterion. If ith alternative is preferred to mth alternative in comparison with jth criterion, then $x_j^i < x_j^m$. Then term $\frac{\max\left(x_j^m\right)-x_j^i}{\min\left(x_j^m\right)}$ indicates the difference in performance scores for criterion j, between ith alternative and the alternative whose score for criterion j is the highest among all the alternatives considered.

Step 2: Calculate the linear preference rating for the input criteria ($\bar{\bar{I}}_i$) using equation (12):

$$\bar{\bar{I}}_i = \bar{I}_i - \min(\bar{I}_i) \tag{12}$$

Step 3: Compute the preference ratings relating them to the beneficial criteria. The aggregate performance for ith alternative on all the beneficial or output criteria is measured using the equation (13):

$$\bar{O}_i = \sum_{h=1}^{H} w_h \frac{x_h^i - \min\left(x_h^m\right)}{\min\left(x_h^m\right)} \tag{13}$$

Where $h = 1,2,\dots,H$ indicates the number of beneficial attributes or output criteria and w_h is calibration constant or weight importance of hth output criteria. The higher an alternative's score for an output criterion, the higher is the preference for that alternative. It can be mentioned that $\sum_{j=1}^{n} w_j + \sum_{h=1}^{H} w_h = 1$. It was considered a $\sum_{h=1}^{H} w_h = 0{,}00375$

Step 4: Calculate the linear preference rating for the output criteria ($\bar{\bar{O}}_i$) using the equation (14):

$$\bar{\bar{O}}_i = \bar{O}_i - \min(\bar{O}_i) \tag{14}$$

Step 5: Compute the overall preference ratings (P_i) as follows in equation (26):

$$P_i = \left(\bar{\bar{I}}_i + \bar{\bar{O}}_i\right) - \min\left(\bar{\bar{I}}_m + \bar{\bar{O}}_m\right) \tag{15}$$

The alternatives are ranked according to the values of the overall preference rating. The best alternative is determined as the one with the minimum value of P_i.

III. I. IV. TOPSIS METHOD

The basic idea of TOPSIS is that the best decision should be made to be closest to the ideal and farthest from the non-ideal [14].Such ideal and negative-ideal solutions are computed by considering the various alternatives. The highest percentage corresponds to the best alternative.

The TOPSIS approach is structured by the following procedure [14]:

Step 1: Normalize the decision matrix n_{ij} by is performed using the equation 16.

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{16}$$

Where x_{ij} is the performance measure of jth criterion in association withith alternative.

Step 2: Sync the weight w_j and the normalized matrix n_{ij}, see equation (17).

$$V_{ij} = n_{ij} \cdot w_j \quad (i = 1,2,\dots,m;\ j = 1,2,\dots,m) \tag{17}$$

Step 3: The ideal solutions (V^+) and nadir solutions (V^-) are determined using (18) and (19):

$$\{V_1^+, V_2^+, \dots, V_n^+\} = \left\{\left(max_i V_{ij} | j \in K\right), \left(min_i V_{ij} | j \in K'\right)\right\}\{i = 1,2,\dots,m\} \tag{18}$$

$$\{V_1^-, V_2^-, \dots, V_n^-\} = \left\{\left(min_i V_{ij} | j \in K\right), \left(max_i V_{ij} | j \in K'\right)\right\}\{i = 1,2,\dots,m\} \tag{19}$$

Where K and K' are the index set of benefit criteria and the index set of cost criteria, respectively.

Step 4: The distance between the ideal and nadir solution is quantified. The two Euclidean distances for each alternative are computed as given by equations (20) y (21):

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^+)^2}\ i = 1,2,\dots,n; \quad i = 1,2,\dots,n \quad (20)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n}(V_{ij} - V_j^-)^2}\ i = 1,2,\dots,n; \quad i = 1,2,\dots,n \quad (21)$$

Step 5: The relative closeness (C_i) is computed by equation (22).

$$C_i = \frac{S_i^-}{S_i^- + S_i^-}\ i = 1,2,\dots,m;\ 0 \le C_i \le 1 \quad (22)$$

The highest C_i coefficients correspond to the best alternatives.

III. I. V. Spearman's rank correlation coefficient

The Spearman's rank correlation coefficient measures the relation among nonlinear datasets. Its purpose is to quantify the strength of linear relationship between two variables. If there are no repeated data values, a perfect Spearman correlation of +1 or −1 occurs when each of the variables is a perfect monotone function of the other [16]. The Spearman's rank correlation is computed by equation (23).

$$R_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \quad (23)$$

Where:
R_s: Spearman's rank coefficient
d_i: Difference between ranks of each case
n: Number of pairs of values

IV. Results

After the determination of the weights of different criteria using the AHP and Entropy methods, these weights were applied to the MCDM methods. The results have been established with COPRAS-G, OCRA, ARAS, TOPSIS and SMART methods. The results have been compared by means of Spearman's rank correlation coefficient in order to determine their convergence and sensibility and ranked the best solutions.

IV. I. Criteria weighting

The comparison among properties of every alternative is in Table 1. The properties identification appears under the name of each property as (LHV), (MC), (D), (AM), (AD) and (VD). The weight of each alternative was established with AHP and Entropy methods. The criteria weighting was firstly implemented by the AHP method to obtain the subjective weights of different evaluation criteria. In Table 2 is can be showed the scale of relative importance used in the AHP method.

Table2. Scale of relative importance

Definition	Intensity of importance
Equal importance	1
Moderate importance	3
Strong importance	5
Very strong importance	7
Extreme importance	9
Intermediate importance	2, 4, 6, 8

Table 3. Comparison among criteria for AHP Method

(LHV)	(MC)	(D)	(AM)	(AD)	(VD)
1	3	3	5	5	7
0,333	1	1	3	3	5
0,333	1	1	3	3	5
0,200	0,333	0,333	1	1	3
0,200	0,333	0,333	1	1	3
0,143	0,200	0,200	0,333	0,333	1

Table 4. normalized decision matrix P_{ij} for entropy method.

Material	(LHV)	(MC)	(D)	(AM)	(AD)	(VD)
1	0,332	0,286	0,050	0,296	0,217	0,420
2	0,350	0,762	0,239	0,327	0,091	0,417
3	0,337	0,381	0,119	0,296	0,139	0,436
4	0,332	0,286	0,045	0,441	0,217	0,420
5	0,550	0,133	0,634	0,339	0,348	0,189
6	0,298	0,267	0,410	0,371	0,594	0,326
7	0,246	0,067	0,075	0,428	0,552	0,366

Table 5. Criteria weighting by the AHP (α_j) and balanced scales entropy (β_j), methods and compromised weighting (w_j) methods.

	(LHV)	(MC)	(D)	(AM)	(AD)	(VD)
α_j	0,425	0,191	0,191	0,078	0,078	0,037
β_j	0,246	0,111	0,026	0,257	0,155	0,204
w_j	0,613	0,125	0,030	0,118	0,071	0,044

IV. II. OCRA Method

Firstly, the aggregate performance of each alternative related to all the input criteria is calculated with equation (11). Applying equation (13), the aggregate performance of the alternatives on all the beneficial or output criteria are then determined and subsequently, the linear preference ratings for the output criteria are calculated. Finally, the overall preference rating for each alternative fuel is determined using equation (15). The detailed computations of this method for a biomass fuel are presented in Table 6. In this method, the ranking fuel alternatives are obtained as 6-1-7-4-3-5-2, which suggests that rice huskattains the top rank. Straw is the second best choice and wood has the last rank.

Table 6. Computation details for OCRA method.

Material	$\bar{I}_i$	$\bar{\bar{I}}_i$	$\bar{O}_i$	$\bar{\bar{O}}_i$	P_i	Rank
1	1,555	0,973	0,003	0,000	0,937	2
2	0,582	0,000	0,009	0,006	0,005	7
3	1,378	0,797	0,004	0,001	0,296	5
4	1,520	0,938	0,003	0,000	0,937	4
5	1,132	0,550	0,010	0,000	0,848	3
6	1,875	1,293	0,003	0,000	0,235	6
7	1,512	0,931	0,009	0,006	1,292	1

IV. III. TOPSIS METHOD

The decision matrix given in Table 1 was normalized using equation (16) for the application of the TOPSIS method and this was multiplied by the compromised weights obtained. In Table 7 is shown the weighted and normalized decision matrix $V_{ij}$for the alternatives for a biomass fuel. The ideal and nadir ideal solutions, determined by equations (18) and (19), are presented in Table 8. The distances from the ideal (S_i^+) and nadir ideal solutions (S_i^-) and the relative closeness to the ideal solution (C_i) are measured using equations (20)–(22). The biomass fuel alternatives could be ranked by the relative degree of approximation and the ranking is shown in Table 9. The ranking of the fuel alternatives are 7-1-5-4-3-6-2. For TOPSIS method wheat grain obtain the first rank for the biomass fuel. In contrast, woodhas the last rank.

Table 7. Weighted and normalized decision matrix, V_{ij} of TOPSIS.

Material	(LHV)	(MC)	(D)	(AM)	(AD)	(VD)
1	0,398	0,288	0,065	0,315	0,232	0,428
2	0,419	0,769	0,309	0,348	0,097	0,425
3	0,403	0,384	0,154	0,315	0,148	0,444
4	0,398	0,288	0,058	0,469	0,232	0,428
5	0,357	0,269	0,531	0,395	0,633	0,332
6	0,294	0,067	0,097	0,455	0,589	0,373
7	0,363	0,135	0,763	0,313	0,337	0,083

Table 8. The ideal and nadir ideal solutions of TOPSIS method.

	(LHV)	(MC)	(D)	(AM)	(AD)	(VD)
V^+	0,257	0,008	0,023	0,037	0,045	0,020
V^-	0,180	0,096	0,002	0,055	0,007	0,004

Table 9. Computation details for TOPSIS method.

Material	S_i^+	S_i^-	C_i	Rank
1	0,047	0,091	0,660	2
2	0,097	0,080	0,452	7
3	0,056	0,086	0,603	5
4	0,050	0,089	0,639	4
5	0,047	0,085	0,642	3
6	0,081	0,095	0,540	6
7	0,044	0,096	0,683	1

IV. IV. SPEARMAN'S CORRELATION COEFFICIENTS

Spearman's correlation coefficients for biomass fuel represent the mutual correspondence among TOPSIS and OCRA methods. The correlation has a value of 1,000 between OCRA and TOPSIS methods.

V. DISCUSSION

The MCDM are an important tool to recognize and identify the best alternative in a bunch of several of them. These methods can adapt to different sort biomass fuel that would affect the final result and that is why these approaches are applied in different areas of science, engineering and management.

In this case, we take advantage of MCDM in order know the best alternative for biomass fuel. In Fig. I is resumed the overall rank of each MCDM method for the different alternatives. It has been observed than OCRA and TOPSIS methods the best biomass fuel alternative is white grain because it has a good LHV and low moisture content. The method validation was correlated by Spearman's coefficients with a value of 1.

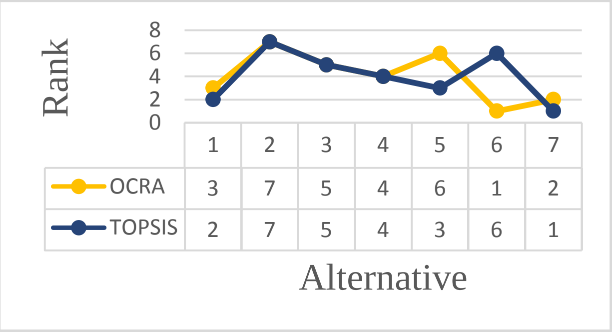

Figure 1. Rank materilas vs. alternative materials for a biomass fuel.

VI. CONCLUSIONS

In this paper the selection problem for a biomass fuel has been solved utilizing a decision model. The model includes the OCRA and TOPSIS methods. Ranking scores which were used to rank the alternative biomass fuel were obtained as results of the methods. The weighting of the fuel properties was performed using the compromised weighting method w_j composes of the AHP and Entropy methods. According to the results of the best alternative OCRA and TOPSIS methods was white grain appear has the best choice for a biomass fuel.

It was validated that the MCDM approach is a viable tool in solving the complex decision problems. Spearman's rank correlation coefficient was found to be very useful in assessment of the correlation between three ranking methods. The model which was developed for the decision of a biomass fuel can be applied on other selection problems.

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