IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 11 February 2023, accepted 1 March 2023, date of publication 16 March 2023, date of current version 21 March 2023.
Digital Object Identifier 10.1109/ACCESS.2023.3254532

RESEARCH ARTICLE

Hybrid Renewable Energy Resources Selection Based on Multi Criteria Decision Methods for Optimal Performance

GAMA ALI, (Student Member, IEEE), HMEDA N. MUSBAH, (Student Member, IEEE), HAMED H. ALY, (Senior Member, IEEE), AND TIMOTHY LITTLE
Department of Electrical and Computer Engineering, Dalhousie University, Halifax, NS B3H 4R2, Canada
Corresponding authors: Gama Ali (Gama.Ali@Dal.Ca) and Hamed H. Aly (Hamed.Aly@Dal.Ca)

ABSTRACT This paper used different Muti-Criteria Decision Analysis (MCDA) techniques to select the best alternative renewable energy sources in Msallata city, southeast of Tripoli, Libya. The selection was based on the commitment from the ministry of Energy in the Libyan government to lower their carbon footprint. The renewable energy sources considered here are solar, wind, and biomass. MCDA is widely used to solve various decision problems based on alternative evaluation. MCDA methods are currently applied in every field and can define any problem, alternatives, and criteria. However, every MCDA technique can give different results. In this paper, four MCDA methods have been tested and evaluated based on the renewable energy sector to find the best alternative. The results suggest that a combination of wind and solar is the most important energy source; solar plants alone are the second most important energy source. The least important energy source in this model is biomass alone. This work is validated using HOMER Pro Software. Many MCDA techniques are applied these days in almost all disciplines, but they may have different results. This work proved that the best MCDA for dealing with renewables for the proposed selection is either The COmplex PRoportional ASsessment (COPRAS) or VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR). COPRAS is a MCDA technique that is developed by Zavadskas, Kaklauskas, and Sarka in 1994, it is applied to maximize and minimize index values. VIKOR is an abbreviation of a Serbian term that means Multicriteria Optimization and Compromise Solution, it ranks and selects from various alternatives with conflicting criteria.

INDEX TERMS Alternative renewable energy sources, COPRAS, MCDA, TOPSIS, fuzzy TOPSIS, VIKOR.

I. INTRODUCTION

The world's population has grown dramatically in the last 50 years; consequently, energy consumption and demand have also increased drastically. In 2010, the globe's energy consumption increased by 5.6%, and this is considered the highest growth in 40 years [1]. The fact that fossil fuels sources are finite as well as the impact they have on the environment, has urged governments and companies to upgrade from conventional fuel sources to renewable ones [2]. From 2023 to 2025, the average annual solar PV installation additions are anticipated to reach 165 GW, which is about 60% of total renewable energy expansion. Moreover, the generation costs of utility scale PV farms are anticipated to decrease in the next few years by 36%, making solar energy the cheapest option to upgrade the electric grid in most countries.

The cost of onshore wind declined by 15% in 2020; on the other hand, the annual offshore wind energy capacity additions are expected to be double the 2020 level between 2023 and 2025 [3]. Approximately 99% of the global power demand is expected to be covered by renewable energy in

The associate editor coordinating the review of this manuscript and approving it for publication was Mostafa M. Fouda.

2025. The electric power that is generated from renewables is expected to increase by more than 9 times in the EU and the UK, and more than three times in the US. In China and India, renewables expected to meet approximately 65% of the electric demand growth [3].

The main sources of energy in Libya are oil and gas, but there are also several thermal power plants in Libya, the most important of which are West of Tripoli (600 MW), East of Tripoli (1400 MW), Misratah (600 MW), and Tobruk (740 MW) [4]. According to General Electricity Company of Libya (GECOL), 99.2% of the generated power in 2004 came from fossil fuels (72.7% from oil and 26.5% from gas respectively) [5]. In 2017, GECOL announced that the generated power was 4900 MW, while the demand exceeded 6500MW, with a 1600 MW deficit. Therefore, the electric grid experienced repetitive power outages in most Libyan regions. Based on the growing energy demand, GECOL also estimated the maximum load to increase to 10,795 MW by 2020, to 14,834 MW by 2030 and to 21,669 MW by 2050, respectively. As a result, the CO_2 and GHG emissions released will increase [4].

With the growing energy demands, the renewable energy department in GECOL proposed some solar and wind power projects in the last decade [6]. The Libyan government has committed to add 30% of its total generation capacity by 2030 from renewables [7]. This paper studies the option of applying wind energy, solar energy, and biomass energy in an area in Msallata, Libya as part of the contribution of GECOL to meet the increasing load demand and to lower the carbon footprint resulted from the use of fossil fuels.

In this paper, various MCDA methods, namely Vise Kriterijumska Optimizacija Kompromisno Resenje (VIKOR), The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Fuzzy TOPSIS and The COmplex PRoportional ASsessment (COPRAS) were applied to evaluate a hybrid energy system based on solar, wind and biomass energy sources. The criteria weights of the MCDA methods were generated using analytic hierarchy method (AHP). The obtained results were compared with HOMER Pro. Software results. The novelty here is to design several models to solve multicriteria decision problems for a hybrid energy system and compare optimization methods (HOMER Pro. Software) with multicriteria decision methods. Biomass feedstock will be used for the first time as a fuel in Libya, where about 99.2% of the fuel used to generate power comes from fossil fuels.

There is not a lot of literature about applying renewable energy sources in Libya. In reference [7], it is concluded that solar and wind energy are the most important renewable energy sources in Libya and could play a major role in covering most of the increased power demand and reducing the Carbon footprint caused by applying conventional fuel. Reference [10] studied the financial and technical challenges that faces utilizing renewable energy resources in Libya. Based on literature review and field visits, it considered solar and wind energy as the main sources of renewable energy. Even though renewable energy technology in Libya is in its early stages, the study revealed the importance of developing the infrastructure of renewable energy sector in Libya to cover the increased power load demand and to lower the consumption of oil and natural gas. In this paper, we assessed our study with the load profile of an area in Msallata city. By means of HOMER Pro software, we determined the net present cost (NPC) of each model, the energy produced, the energy consumed, the emissions and many other results that we will not discuss in this study. In the results and discussion chapter, we will discuss the energy produced, the energy consumed, and the cost benefit of each energy source applied in this study. In the future work, we will add waves and tidal to the study to know if they are of importance as of solar and wind.

II. LITERATURE REVIEW

This paper presents a study on some renewable energy sources and some MCDA techniques. In references [7] and [8], the options available to apply some renewable energy sources to the Libyan power grid are studied. Veleba and Buhawa [9] investigated initial, steady state and optimization load flow analysis to the transmission lines of the Libyan power grid by adding large scale wind farms. Mohamed investigated in [10] the financial and technological difficulties facing applying renewable energy resources in Libya. Introduced some recommendations to enhance the renewable energy. Wang et al. applied in [11] a hybrid Fuzzy AHP (FAHP) and TOPSIS to select wind power plant from seven different locations in Vietnam. Gao et al. [12] presented a MCDA technique for site selection of CAES project based on probabilistic language term sets (PLTSs) and regret theory, applied entropy weight method to weight the criteria and concluded in a case study in China that Yungang Mine of Datong Coal Mine Group is the best CAES project site location.

Li et al. introduced in [13] multicriteria decision-making framework for DPVPS site selection along high-speed railway. Presented the power consumption capacity of high-speed railway TPSS and impact on high-speed railway TPSS. A case with sensitivity analysis is used to verify the MCDA framework for DPVPS site selection along high-speed railway. Abdel-Basset et al. proposed a new hybrid methodology for the selection of offshore wind power station location (OWPS) combining the AHP and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE)-II methods in the neutrosophic environment [14]. Aly proposed in [15] different accurate hybrid models to forecast the wind speed and power based on neuro Wavelet, time series and Recurrent Kalman Filter to ameliorate the overall system accuracy. In [16], a hybrid optimized model of Adaptive Neuro-Fuzzy Inference System (ANFIS), Recurrent Kalman Filter (RKF) and Neuro-Wavelet (WNN) was presented to forecast wind power based on data taken from doubly fed induction generation model.

Mousavi-Nasab and Sotoudeh-Anvari [17] conducted a comparative analysis about the rank reversal problem in COPRAS, TOPSIS and VIKOR methods.

Introduced their importance in material selection and the usefulness of rank reversal method when a criterion is removed from or added to a decision process. Joshi introduced in [18] a novel bi-parametric exponential information measure based on Intuitionistic Fuzzy Sets (IFSs). Presented a new MCDA algorithm based on TOPSIS and the proposed bi-parametric measure. Applied the algorithm in detecting machine malfunctioning by means of a numerical example. Rosso-Cerón et al. presented in [19] a novel algorithm based on fuzzy multi-criteria decision-making methods (FMCDM) based on a mixed-integer linear model to impose solar and wind energy into the Colombian energy-mix. Özcan et al. [20] studied the maintenance scenarios of 14 high criticallity level equipment in a large-scale hydroelectric power plant in Turkey. They applied AHP and TOPSIS techniques to obtain the criteria and determine the ranking of the equipment, respectively. They built an artificial neural network (ANN) model by using 11-years fault data for selected equipment groups and estimated the possible fault dates.

Krishankumar et al. presented amalgamated approach to deal with MCDA under the probabilistic hesitant fuzzy information (PHFI) features. Also, ranked the PHFI with COPRAS method. The applied technique has been implemented through a case study of cloud vendor selection and the results has been validated with various existing techniques' results [21]. Soltaniyan et al. developed in [22] a combined version of MCDA and multi-agent modelling technique (MAMT) to attain the maximum possible profits of an intended renewable generation plan and to enhance the electricity market indices. Applied multi-agent fuzzy Q-learning electricity market modelling approach combined with TOPSIS as a new technique to enhance renewable energy for the first time in the literature. The proposed technique is validated on the IEEE 30-bus test system.

Soha and Hartmann [23] presented an GIS-based site suitability to support site selection for the power-to-gas (PtG) technology. The results obtained show that centralized PtG systems are favored over regular PtG installments in all biogas plant sites. Wang et al. applied TOPSIS method to analyzes the hydropower generation efficiency in Canada from power generating potential viewpoint, profitability, environmental profits and social responsibility, respectively [24]. Ribeiro et al. [25] presented long-term strategic MCDA technique composed of a set of thirteen criteria to evaluate a set of five hypothetical scenarios drawn for the Portuguese electricity generation system in 2020. Zhao and Li presented a novel hybrid framework to support sustainable development of thermal power. Applied fuzzy Delphi method to recognize 22 final criteria. Introduced a hybrid evaluation model that operates in the fuzzy environment based on the analytic network process (ANP) and TOPSIS. Validated the proposed framework with a case study from the China Huaneng Group Corporation [26].

Dhiman and Deb presented in [27] a fuzzy-based MCDA technique for three wind farm sites in Massachusetts. Evaluated four alternatives for four penalty costs by actual and predicted wind power that are normalized further. Applied Fuzzy TOPSIS and Fuzzy COPRAS as a modified TOPSIS and COPRAS techniques to attain the ranking under fuzzy environment. Hosseini Dehshiri and Hosseini Dehshiri [28] applied a combined technique of Geographic Information System (GIS) and MCDA to specify an area to build wind farms to produce hydrogen in Yazd province in Iran. Feyzi et al. introduced in [29] a new decision-making approach to determine the criteria of establishing municipal solid waste incineration (MSWI) power plant to increase the sustainability in the north of Iran by applying the decision-making trial and evaluation laboratory (DEMATEL) combined with fuzzy analytic network process (FANP) technique and GIS. Zlaugotne et al. in [30] applied five MCDA techniques to find the best renewable energy source in Latvia. In PROMETHEE-GAIA, TOPSIS and VIKOR, hydropower has the highest rank. On the other hand, the best alternative energy source with COPRAS and MULTIMOORA was Solar PV.

Wang et al. applied in [31] data envelopment analysis (DEA), FAHP, and TOPSIS to find the most feasible location to build a solar power plant in Vietnam. Rehman et al. applied MCDA to select the best wind power plant location to invest it in the gulf region [32]. Wu et al. [33] introduced a two-stage location decision-making structure to select a site in Hezhang County for distributed wind power coupled hydrogen storage (DWPCHS). Conducted empirical research about applying DWPCHS in this site. Zambrano-Asanza et al. presented a novel technique to specify optimal sites for solar power plants that are connected to the medium-voltage level in the Ecuadorian power grid, applied GIS based MCDA and spatial overlay with electric load [34]. Ali et al. presented in [35] a novel hybrid MCDA approach applying an aggregated weighting and ranking method to promote PGTs based in Bangladesh. From the six existing PGTs, gas was the best and wind was the worst. In terms of all PGTs' options, Solar PGT was the most feasible option. In [36], a sophisticated hybrid deep learning clustered models is presented to forecast wind speed and power applying different artificial intelligent systems for optimal performance.

Rahmati and Sanaye-Pasand [37] presented a general protection scheme to alleviate the disadvantages of the power transformer relays. This scheme presented a novel MCDA based on fuzzy logic. The developed power transformer protection (DPTP) relay reinforces the sensitivity and reliability of the power transformer protection. Urošević and Marinović presented a framework to rank small hydropower projects to decision makers in Bosnia and Herzegovina based on various criteria. They applied PROMETHEE technique to rank 24 small hydropower plants and used AHP to obtain the weights of main criteria [38]. Ehteram et al. applied kidney algorithm technique to optimize Karun reservoir operation in hydropower plant project [39]. Waewsak et al. applied in [40] an GIS-AHP technique to specify suitable locations in Thailand to build energy facilities running with green energy, namely with para rubber trees as a biomass resource.

III. RESEARCH DEVELOPMENT

In this work, the authors introduced four different MCDA techniques as a way of validation for the proposed work to select the optimal energy source to supply power energy to a city known to have very good solar irradiation and wind speed. The load profile data for Msalla city has been collected from GECOL, where customers have different peaks at different times, see figure 1. A load profile is a chart illustrating the variation in the electrical load versus time. It varies based on customer type (commercial, industrial, or residential), temperature and holiday seasons. Commercial and industrial customers have higher load demand in the morning and at noon, while residential customers may consume more power in the afternoon and evening time.

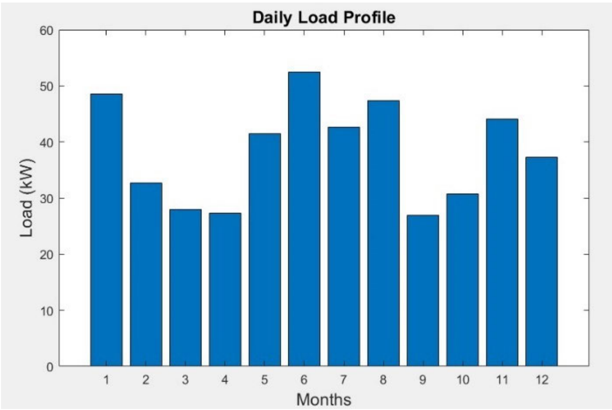

FIGURE 1. Load profile for an area in Msallata city.

The proposed models are evaluated and validated by applying real data and using HOMER Pro software for calculating the overall cost coming from different techniques and the emissions emitted by applying various power sources. Based on the analysis done, a hybrid wind and solar plant is the most important energy source, followed by solar plant as the second most important energy source. The third best alternative was wind model based on three MCDA techniques; fuzzy TOPSIS technique considers the wind energy model as the best fourth alternative source. PV, wind, and biomass hybrid model is considered the fourth most important energy source in three MCDA techniques, fuzzy TOPSIS technique considers the wind energy model as the best third alternative source. Biomass model has the least importance in this model.

A. CRITERIA WEIGHTING

The criteria weights are calculated using AHP weighting method. Thomas L. Saaty developed AHP in the 1970s to model some decision-making processes through pairwise comparisons and experts' judgements to obtain priority scales, it has been applied extensively since then, and is currently applied in decision making problems [41]. For more details, see [42].

Table 1. depicts the criteria applied to evaluate the attributes. Msallata city is currently supplied with power from the Libyan grid, which is generated from conventional fuel. HOMER Pro software is applied to evaluate the attributes for the hybrid system.

TABLE 1. Criteria used to evaluate the attributes.

	Name	Unit
F1	Cost of Energy (COE)	$/kWh
F2	Operating and Maintenance (O&M)	$/year
F3	Total Fuel Consumption (t/yr)	Ton/year
F4	Production (pr)	kWh
F5	Lifetime (lt)	Years

TABLE 2. Alternative power sources.

	Name
A1	Wind
A2	PV
A3	Biomass
A4	Wind + Biomass
A5	PV + Biomass
A6	Wind + PV
A7	Wind + PV + Biomass

Table 2. shows the power sources suggested in this journal. They are either one power source or a combination of two or more.

Table 3. shows the alternatives and the attributes. The data in this table is the decision matrix data that will be normalized and applied in the four MCDA techniques applied in this paper.

TABLE 3. Alternatives and attributes.

Alternatives	Attributes				
	COE	O&M	Ton/yr	pr	lt
A1	1.78	6000	0	319063	20
A2	1.12	1500	0	218313	17
A3	5.96	18900	0.411811	157500	25
A4	2.82	4500	0.021571	167782	22
A5	2.63	3500	0.022225	132300	20
A6	0.852	3000	0	186501	18
A7	2.41	2000	0.011112	128494	20

B. MULTICRITERIA DECISION ANALYSIS METHODS

Multi-criteria decision analysis MCDA is a methodology that deals with various conflicting criteria in decision making problems, in almost every discipline, when different or conflicting criteria are considered at the same time to rank or make a decision (or objectives) need to be considered together, to rank or choose between the alternatives being evaluated [43].

1) VIKOR

The VIKOR method is an MCDA technique that has been developed by Serafim Opricovic in his Ph.D. dissertation in 1979 to solve decision problems that have conflicting or incommensurable criteria, assuming that decision is justifiable for conflict problems. The solution desired is to be closest to the ideal, and all alternatives are determined based on established criteria. VIKOR ranks alternatives and determines the solution named compromise that is the closest to the ideal. Figure 2. depicts the steps of VIKOR technique, for more details, see [44].

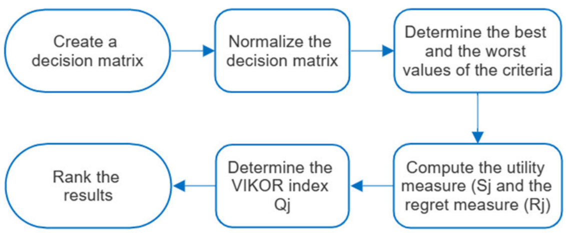

FIGURE 2. **Steps for VIKOR technique.**

VIKOR steps:

1- Create the decision matrix

$$X = \begin{bmatrix} I_{11} & \cdots & I_{1n} \\ \vdots & \ddots & \vdots \\ I_{m1} & \cdots & I_{mn} \end{bmatrix} \tag{1}$$

where I_{11} to I_{1n} are the attributes and I_{11} to I_{m1} are the Alternatives.

2- Determine the normalized decision matrix:

$$k_{ij} = \frac{I_i^j}{\sqrt{\sum_{i=1}^{m} \left(I_i^j\right)^2}} \tag{2}$$

where $i = 1, 2, \ldots, m; j = 1, 2, \ldots, n$.

3- Determine utility measure U_i and regret measure R_i. When decisionmakers are not able to express their preference, they compromise their solution by a maximum group utility (represented by min U_i) of the majority, and by a minimum individual regret (represented by min R_i) of the opponent. U_i and R_i are boundary measures to formulate the rank.

Utility measure for beneficial attribute:

$$U_i = \sum_{i=1}^{n} w_i \left[\frac{(k_{ij})_{\max}? - (k_{ij})}{(k_{ij})_{\max} - (k_{ij})_{\min}} \right] \tag{3}$$

Utility measure for non-beneficial attribute:

$$U_i = \sum_{i=1}^{n} w_i \left[\frac{(k_{ij}) - (k_{ij})_{\min}}{(k_{ij})_{\max} - (k_{ij})_{\min}} \right] \tag{4}$$

Regret measure for beneficial attribute:

$$R_i = Maximum\ of \left\{ w_i \left[\frac{(k_{ij})_{\max} - (k_{ij})}{(k_{ij})_{\max} - (k_{ij})_{\min}} \right] \right\} \tag{5}$$

Regret measure for non-beneficial attribute:

$$R_i = Maximum\ of \left\{ w_i \left[\frac{(k_{ij}) - (k_{ij})_{\min}}{(k_{ij})_{\max} - (k_{ij})_{\min}} \right] \right\} \tag{6}$$

4- Compute the Qi value:

$$Q_i = v \left[\frac{U_i - (U_i)_{\min}}{(U_i)_{\max} - (U_i)_{\min}} \right] + (1 - v) \left[\frac{R_i - (R_i)_{\min}}{(R_i)_{\max} - (R_i)_{\min}} \right] \tag{7}$$

v can take any value between 0 and 1, in our case v considered 0.5.

5- Rank Q_i, the rank will be in descending order. Highest Q_i value represents the best alternative.

2) TOPSIS

TOPSIS technique was developed by Hwang and Yoon in 1981 to find the closest alternatives to the ideal solution [41]. Figure 3. depicts the steps of TOPSIS technique, for more details, see [45].

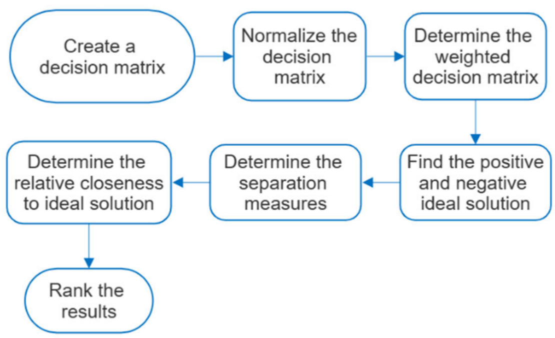

FIGURE 3. **Steps for TOPSIS technique.**

TOPSIS steps:

1- Determine the decision matrix

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1j} \\ \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} \end{bmatrix} \tag{8}$$

2- Establish the normalized decision matrix:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} (x_{ij})^2}} \tag{9}$$

where $i = 1, 2, \ldots, m; j = 1, 2, \ldots, n$.

3- Determine the weights (AHP used in this paper)

4- Determine the weighted normalized decision matrix:

$$v_{ij} = w_j \times r_{ij} \tag{10}$$

5- Compute ideal best (v_j^+) and ideal worst (v_j^-). In non-beneficial attributes, ideal best will be the least value, and ideal worst will be the highest value. In the case of beneficial attributes, the highest value is considered ideal best, while the lowest value is considered ideal worst.

$$\{V_1^+, \ldots, V_n^+\} = \left\{(\max_i V_{ij} | j \in K), (\min_i V_{ij} | j \in K') | i = 1, 2, \ldots, m\right\} \tag{11}$$

$$\{V_1^-, \ldots, V_n^-\} = \left\{(\min_i V_{ij} | j \in K), (V_{ij} | j \in K') | i = 1, 2, \ldots, m\right\} \tag{12}$$

where K is the index set of benefit criteria and K' is the index set of cost criteria.

6- Compute the separation measure for each row: Positive ideal separation:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \tag{13}$$

Negative ideal separation:

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \tag{14}$$

7- Determine the relative closeness to the ideal solution:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{15}$$

8- Rank the results: the higher value will get the first in rank.

3) FUZZY TOPSIS

TOPSIS Fuzzy TOPSIS method was developed by Chen-Tung Chen in 1997 in a journal titled Extensions of the TOPSIS for Group Decision-Making under Fuzzy Environment. Chen extended TOPSIS with triangular fuzzy numbers, and he proposed a vertex technique to measure the distance between two triangular fuzzy numbers. Figure 4. depicts the steps of fuzzy TOPSIS technique, for more details, see [46].

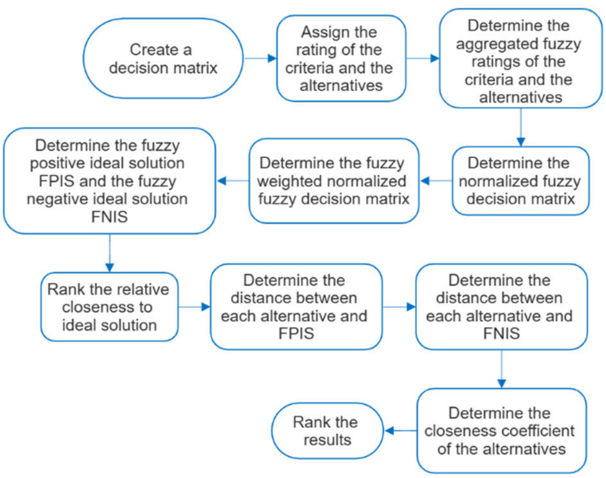

FIGURE 4. Steps for fuzzy TOPSIS technique.

Chen presented a vertex technique to measure the distance between two triangular fuzzy numbers [44]. If $\tilde{x} = (a_1, b_1, c_1), \tilde{y} = (a_2, b_2, c_2)$ are two different triangular fuzzy numbers, then:

$$d(\tilde{x}, \tilde{y}) = \sqrt{\frac{1}{3}[(a_1 - b_2)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2]} \tag{16}$$

The following steps are taken when fuzzy TOPSIS is applied [44]:

1- Collect the subjective evaluations of the decision maker on the weights based on the importance of each criterion. Say, we have decision makers with m members, the fuzzy rating of the m^{th} group about alternative O_i and criterion B_i is represented as:

$$F_{ij}^m = \left(a_{ij}^m, b_{ij}^m, c_{ij}^m\right) \tag{17}$$

and the weight of criterion B_j is represented as:

$$\tilde{w}_{ij}^m = \left(w_{j1}^m, w_{j2}^m, w_{j3}^m\right) \tag{18}$$

2- Determine the aggregated fuzzy ratings for each alternative and the aggregated fuzzy weights for every criterion.

3- The aggregated fuzzy ratings $\tilde{F}_{ij} = \left(a_{ij}, b_{ij}, c_{ij}\right)$ are determined as follows:

$$a_{ij} = \left\{a_{ij}^m\right\}, \; b_{ij} = \frac{\sum_{m=1}^{m} b_{ij}^m}{m}, \; c_{ij} = \left\{c_{ij}^m\right\} \tag{19}$$

The aggregated fuzzy weights $\tilde{w}_j = \left(w_{j1}, w_{j2}, w_{j3}\right)$ are calculated by formulas:

$$w_{j1} = \left\{w_{j1}^m\right\}, \; w_{j2} = \frac{\sum_{m=1}^{m} w_{j2}^m}{k}, \; w_{j3} = \left\{w_{j3}^m\right\} \tag{20}$$

4- Measure the normalized fuzzy decision matrix $\tilde{R} = [\tilde{r}_{ij}]$. For benefit criteria

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}\right), c_j^+ = \{c_{ij}\} \tag{21}$$

Or for non-benefit (cost) criteria

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), a_j^- = \{a_{ij}\} \tag{22}$$

5- Determine the weighted normalized fuzzy decision matrix:

$$\tilde{V} = (\tilde{v}_{ij}) \tag{23}$$

where $\tilde{v}_{ij} = \tilde{r}_{ij} \times w_j$

6- Determine the Fuzzy Positive Ideal Solution (FPIS) (A^+) and Fuzzy Negative Ideal Solution (FNIS) (A^-).

$$A^+ = \left(\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+\right) \tag{24}$$

$$A^- = \left(\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-\right) \tag{25}$$

7- Calculate the distance from each alternative to the FPIS (d_i^+) and to the FNIS (d_i^-).

$$d_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+) \tag{26}$$

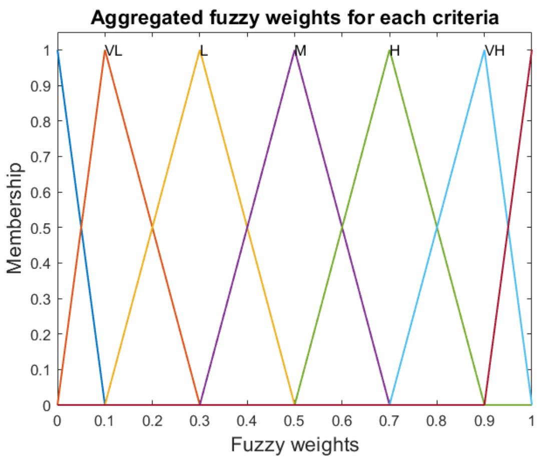

FIGURE 5. Aggregated fuzzy weights for each criterion.

TABLE 4. The fuzzy weights for each criteria.

Importance	Symbol	Fuzzy weight
Very low	VL	(0, 0.1, 0.3)
Low	L	(0.1, 0.3, 0.5)
Medium	M	(0.3, 0.5, 0.7)
High	H	(0.5, 0.7, 0.9)
Very high	VH	(0.7, 0.9, 1)

$$d_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \tag{27}$$

8- Determine the closeness coefficient CC_i for every alternative.
For every alternative O_i, CC_i is calculated as follows:

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{28}$$

9- Rank CC_i in descending order. Highest closeness coefficient will be considered the best alternative.

4) COPRAS

The COmplex Proportional Assessment method was developed by Zavadskas, Kaklauskas and Sarka in 1994 to evaluate the maximum and minimum index values and their effect on the attributes. Figure 6. depicts the steps of COPRAS technique, for more details, see [47].

COPRAS steps

1- Create the decision matrix: The decision matrix and the weights for the criterions are expressed as follows:

$$D = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{29}$$

$$w_j = [w_1 \ldots w_n]\, where \sum\nolimits_{j=1}^{n} (w_1 \ldots w_n) = 1 \tag{30}$$

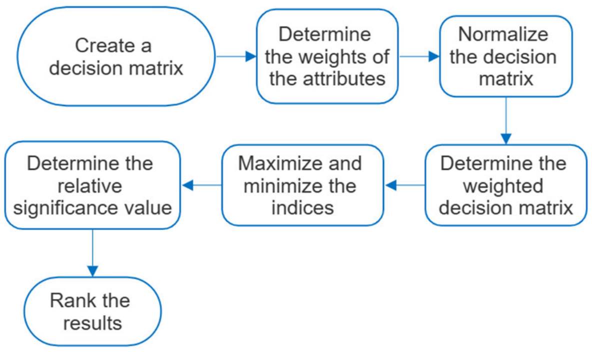

FIGURE 6. Steps for COPRAS technique.

2- Normalize the decision matrix:

$$n_{ij} = \frac{x_{ij}}{\sum\limits_{j=1}^{n} x_{ij}} \tag{31}$$

3- Obtain the weighted normalized decision matrix:

$$N_{ij} = w_j \times n_{ij} \tag{32}$$

4- Compute the sum of the benefit criteria values:

$$B_i = \sum_{j=1}^{k} N_{ij} \tag{33}$$

5- Determine the sum of the cost criteria values:

$$C_i = \sum_{j=k+1}^{m} N_{ij} \tag{34}$$

6- Compute the relative significance of each alternative:

$$Q_i = B_i + \frac{\min(C_i) \times \sum_{i=1}^{n} C_i}{\mathrm{C_i} \times \sum_{i=1}^{n} \left(\frac{\min(C_i)}{C_i}\right)} \tag{35}$$

7- Determine the utility degree (performance index) of each alternative:

$$UD_i = \frac{Q_i}{\max(Q_i)} \times 100\% \tag{36}$$

IV. CASE STUDY

Even though Libya is very rich in solar and wind power, about 99.2% of the electricity is generated from fossil fuels. The Libyan grid has experienced a lot of power outages recently due to the aging of the existing network, lack of developments and increasing load demand. One of the solutions to solve this issue is adding some renewable energy sources to the grid. This paper conducts research on applying some renewable energy sources in a city called Msallata, located to the southeast of Tripoli, Libya. This city known to have very good wind speed according to GECOL. Four MCDA approaches, namely VIKOR, TOPSIS, Fuzzy TOPSIS and COPRAS are applied to find the optimal renewable energy source to provide the city with electricity. HOMER Pro software using wind, solar and biomass sources is applied to validate the results determined by MCDA techniques.

TABLE 5. Monthly average of wind speed in (m/s) in some Libyan cities during 1985 – 1995. [7].

Cities	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Avg
Benina	4.3	4.8	5.7	6.2	5.9	6.0	5.8	5.3	5.1	5.0	4.8	4.4	5.3
Ejdabia	2.2	2.8	3.9	3.6	3.6	3.4	3.5	3.0	2.7	2.3	2.0	2.0	2.9
Sorman	3.4	2.8	3.0	3.4	3.3	3.2	3.0	2.7	2.8	2.7	2.6	2.8	3.0
Zuara	4.5	4.5	5.2	5.4	5.3	5.0	4.4	4.5	4.8	4.4	4.0	4.2	4.7
Sirt	5.1	5.3	5.5	5.6	5.3	4.9	4.3	4.3	4.7	4.7	4.6	4.9	4.9
Mesrata	5.2	5.3	6.1	5.7	5.4	5.0	4.2	4.1	4.6	4.5	4.8	5.3	5.0

TABLE 6. Daily average of total radiation in ($kWh.m^2$) during 1982 – 1988 [7].

Cities	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Avg
Tripoli	2.95	3.87	5	5.97	6.45	7.09	7.05	6.47	5.48	4	3.15	1.83	4.94
Gath	4	4.8	4.7	6.3	6.3	6.6	6.8	6.3	5.8	5.1	4.1	3.5	5.36
Jalo	3.66	4.54	5.37	6.56	6.74	7.16	7.17	6.74	5.74	4.83	3.86	3.44	5.48
Sabha	4.18	4.88	5.81	6.68	6.65	7.35	7.26	6.96	6.51	5.56	4.75	3.97	5.88
Shahat	2.3	2.72	3.93	5.45	6.05	6.73	6.72	6.14	4.67	3.59	2.69	1.97	4.41
Hon	3.54	4.22	5.1	6.19	6.61	7.06	7.09	6.69	5.91	4.72	3.8	3.19	5.34
Al-Kovra	4.43	5.38	6.04	6.86	7.24	7.43	7.25	7.19	6.45	5.67	4.7	3.99	6.05
Al-Quryat	3.55	4.63	5.65	6.61	6.75	7.12	7.39	7.02	5.45	4.32	3.47	3.2	5.43
Al-Jagbob	3.8	4.7	5.59	6.71	7.1	7.67	7.66	7.1	6.22	5.13	4	3.51	5.77

TABLE 7. Random consistency index.

N	3	4	5	6	7	8	9	10	11	12	13	14	15
RCI	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

A. RESOURCE ASSESSMENT

The load profile for Msallata city is taken from the GECOL record. HOMER Pro software is applied to estimate the criteria for the subjected model. Because they are intermittent in nature, solar panels and wind farms are usually connected with back-up generators to avoid any power deficiency. The fuel source for the generator in our current model is biomass.

1) WIND ENERGY SOURCE

The average wind speed in Libya is varying from 6 m/s to 7.5 m/s at 40 m height. This huge wind energy source is distributed over an area of 1,750,000 km^2 and can supply Libya and Europe with a huge amount of electric power [6]. Homer Pro Software is applied to download the monthly average wind speed data in this paper, figure 7. HOMER Pro software download such data from NASA Surface meteorology and Solar Energy.

Figure 8 depicts a 100-kW turbine power curve, where the cut-in speed is 4 m/s and the cut-out speed is 24 m/s, and the rated power output between 10 and 15 m/s.

The wind power formula could be estimated using this equation [48]:

$$P = \frac{1}{2}\rho.A_s.C_p V^3 \epsilon_g \epsilon_b \tag{37}$$

where, ρ is the density of the air in kg/m^3,

A_s is the swept area of the rotor in m^2,

C_p is the coefficient performance,

V is the velocity of the wind speed in (m/s),

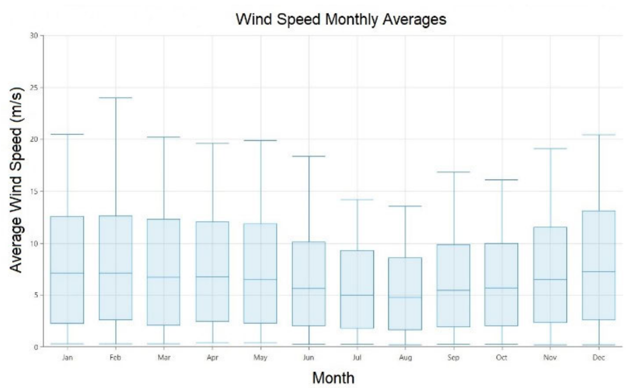

FIGURE 7. Monthly average wind speed for Msallata city determined by HOMER.

ϵ_g is the efficiency of the generator,

ϵ_b is the efficiency of the gear box bearing.

Table 5 depicts the monthly average wind speed in (m/s) in some Libyan cities in the period from 1985 to 1995, while figure 9 depicts the daily profile wind speed for Msallata city determined by HOMER.

2) SOLAR ENERGY SOURCE

The average solar radiation in Libya is about 7.5 kWh/m^2/day, that is between 3000 and 3500 sunshine hours per year [6]. HOMER Pro Software is applied to get the solar

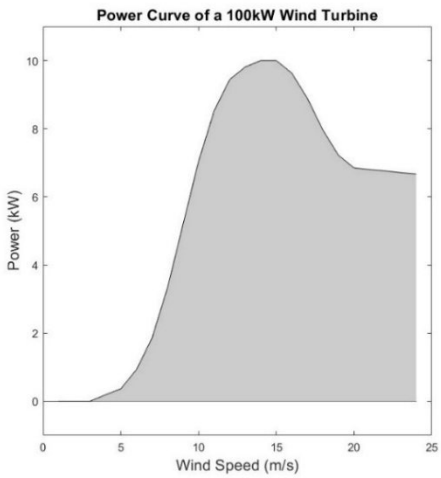

FIGURE 8. 100 kW Wind turbine power curve.

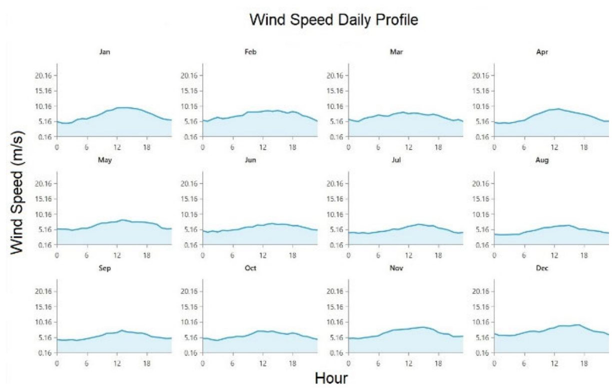

FIGURE 9. Daily profile wind speed for Msallata city determined by HOMER.

data used for this paper, which in return downloaded from NASA Surface meteorology and Solar Energy.

The annual energy of any installed PV system could be estimated using the following equation [46]:

$$E_{an}= 365\times P_{pk} \times rd_p \times R_{d,g} \tag{38}$$

where, E_{an} is the annual energy for the power generated in kWh, P_{pk} is the peak power of the installed equipment in kilowatts (kW), rd_p is the system performance's ration or derating factor and $R_{d,g}$ is the average of daily global radiation in watthours (wh).

Table 6. depicts the daily average of total radiation in (kWh.m^2) for some Libyan cities in the period from 1982 to 1988. Figure 10 depicts the daily profile solar irradiation for Msallata city determined by HOMER.

3) BIOMASS

Using biomass to generate heat and power is increasing rapidly both nationally in Canada and internationally, and it is driven by governments and decision makers wanting to lower the carbon footprint caused by applying conventional fuels.

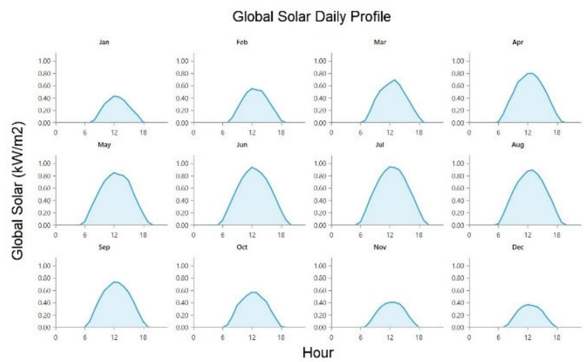

FIGURE 10. Daily profile solar irradiation for Msallata city determined by HOMER.

Global biomass energy consumption is expected to increase by 2.3% annually until 2030 [49]. In this paper, HOMER Pro Software applied biomass feedstock as a backup generator to supply power when there is not enough wind speed or solar irradiation to generate it.

HOMER Pro Software allows users to model generators to run most biomass feedstock types. The software allows users to model biomass gasification, the biogas fuel and the biogas fueled or cofired generator. Users have the option to specify the biomass capacity and price under biomass resource menu. In case the biomass feedstock is raw material, it needs to be converted to biogas first by means of gasification, then it can be burned in a biogas or cofired generator.

V. RESULTS AND DISCUSSION

The AHP method is applied to determine the weights of the criteria, pairwise comparison is made by assessing the importance of the criterion over the other criterion and the results are illustrated in Table 8. In pair comparison technique, the value 1 indicates that both criteria have equal importance, values 3, 5, 7 and 9 represent low, moderate, strong, and very strong importance, respectively. And for opposed criteria, comparison values are proportionally opposed. After determining the criteria weight (w_{ij}), it is very important to verify that the summation of the weights equal 1 (w_{ij}= 1). With regards to the consistency index, the consistency ratio should be less than or equal to 0.1 to assume that the matrix is reasonably consistent.

In the proposed model, the consistency ratio was 0.054153, which is less than 0.1; so, we can consider the matrix as reasonably consistent.

Table 7. depicts the random consistency index, where the numbers 1 and 2 are omitted because their RCI value equals zero. See Saaty [50].

Table 9 shows each criterion and their importance, where beneficial considered when maximum value is desired while non-beneficial for minimum value consideration.

Figure 11 depicts all criteria and their weights. The most important criteria are COE with 50.3% weight, followed by lifetime with 26%, production with 13.4% and CO_2 emissions

TABLE 8. Pairwise comparison matrix.

	COE ($/kWH)	Production (KWH)	O&M ($/yr)	Lifetime	CO_2 emissions
COE ($/kWh)	1	5	9	3	7
Production (KWH)	0.20	1	5	0.33	3
O&M ($/yr)	0.11	0.20	1	0.14	0.33
Lifetime	0.33	3	7	1	5
CO_2 emissions	0.14	0.33	3	0.20	1

TABLE 9. Pairwise comparison matrix.

Criteria	Unit	Attributes
Cost of Energy	$/kWh	Non-beneficial
Operating and Maintenance	$/years	Non-beneficial
CO2 Emissions	Ton/year	Non-beneficial
Production	kWh	Beneficial
Lifetime	Years	Beneficial

with 6.8%, respectively. The less important criterion is operating and maintenance with 3.5% weight.

Table 10. depicts the rank of all power sources applied for Msallata city based on all techniques applied. The rank will be based on the number of power sources applied, in this case will be from 1 to 7 based on their importance, where 1 is the most important and 7 is the less important.

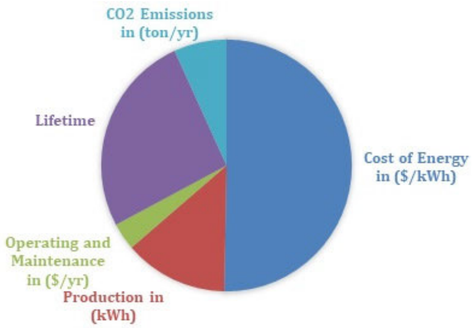

FIGURE 11. Pie chart of the weight of each criterion.

The novelty of the proposed work is to assess the proposed site performance based on four different techniques to choose the best combination of renewables towards minimizing the generation cost and CO_2 emissions. Based on the results, we can conclude that a combination of wind and solar energy source is the most important energy source because all the techniques ranked it as first. Solar energy is second in the row according to all techniques applied. The wind energy source is in third place in the VIKOR, TOPSIS and COPRAS methods, whereas Fuzzy TOPSIS put it in fourth place. Fuzzy TOPSIS technique rank the combination of Solar, wind, and biomass as third. VIKOR, TOPSIS and COPRAS techniques put the combination of Solar, wind, and biomass in fourth place, whereas Fuzzy TOPSIS considers wind energy as fourth in the rank. The less important energy source in the area under study is Biomass based on all techniques applied.

TABLE 10. The rank of the power sources based on each technology applied.

	Technique Applied				
Power source	VIKOR	TOPSIS	Fuzzy TOPSIS	COPRAS	HOMER Pro
Wind	3	3	4	3	3
PV	2	2	2	2	2
Biomass	7	7	7	7	7
Wind + Biomass	5	6	5	5	5
PV + Biomass	6	5	6	6	6
Wind + PV	1	1	1	1	1
Wind + PV + Biomass	4	4	3	4	4

HOMER Pro Software is applied to determine the technical and cost-benefit analysis of all the models. In the next paragraphs, analysis about the best four models is discussed.

Technical analysis: Based on the simulation results obtained from HOMER, the hybrid wind solar model is the most feasible option, where 71.3% of the produced energy came from wind (132,943 kWh/yr), the rest 28.7% is produced from solar (53,558 kWh). The energy consumed is 60,293 kWh. The second feasible model is the PV model, where the energy produced is 218,313 kWh/yr and the energy consumed is 60,281 kWh/yr.

The third model in the rank is the wind model, where the energy production reached 319,063 kWh and the consumed energy was 60,282 kWh. The hybrid system that is composed of solar, wind and biomass came in the fourth rank with energy production of 128,494 kWh/yr, where 55.3% (71,067 kWh/yr) of the energy produced is from solar, 41.4% (53,177 kWh/yr) is from wind and the rest 3.31 % (4,250 kWh/yr) is produced from biomass. The consumed energy as of the previous models is 60.330 kWh.

Cost-benefit Analysis: The main advantage of applying renewable energy is the absence of fossil fuel costs. Moreover, PV and wind energy plants have low operation and maintenance costs compared to conventional fuel plants. The total net present cost (NPC) of the hybrid wind and solar model is $663,707.80 and the levelized cost of energy (COE) is $0.8515. The total NPC of the solar model is $874,808.90 and the levelized COE is $1.12. In the wind model, the total NPC was $1,388,200 and the levelized COE was $1.78, while the total NPC of the hybrid wind, solar and biomass model reached $1,883,473 and the levelized COE is $2.41.

VI. CONCLUSION

In this work, four different MCDA techniques were applied to rank the power energy sources based on their importance. Although all MCDA techniques applied use different aggregation functions and different normalization techniques, they try to get results close to the ideal solution. A validation has been done through an optimization technique (HOMER Pro software). Based on the results, some renewable energy sources could be added to the Libyan grid to face the big energy demand, to improve the electric power service and lower the carbon footprint occurring by apply conventional energy sources. Biomass could be applied in combination with wind and solar energy sources.

Based on the results, all the techniques applied rank a hybrid energy system composed of wind and solar, and a solar farm as the best and the second-best alternative, respectively. All the techniques applied considered a wind farm as the third best alternative, except fuzzy TOPSIS considered wind energy alone as the fourth option in its rank. All the techniques agree that biomass alone is the least attractive option.

To validate the results, HOMER Pro software is applied. Based on the results obtained from HOMER, VIKOR and COPRAS, a hybrid energy system composed of wind and PV, PV energy system, Wind energy system, a hybrid energy system composed of wind, PV and biomass, a hybrid energy system composed of wind and biomass, a hybrid energy system composed of PV and biomass, a biomass energy system, are ranked, first, second, third, fourth, fifth, sixth and seventh, respectively. Based on that comparison of selection and the constraints used in this research we conclude that the best MCDAs to select a hybrid energy system in our case are VIKOR and COPRAS. Both gave reasonable results compared to a realistic scenario used from HOMER Pro software.

The low importance of biomass alone as a feedstock to generate power in Libya is linked to the fact that Libya is rich of solar and wind power. Because solar and wind power are intermittent in nature, biomass feedstock could be applied as a fuel for backup generation.

REFERENCES

[1] J. Milano, H. C. Ong, H. H. Masjuki, W. T. Chong, M. K. Lam, P. K. Loh, and V. Vellayan, "Microalgae biofuels as an alternative to fossil fuel for power generation," *Renew. Sustain. Energy Rev.*, vol. 58, pp. 180–197, May 2016, doi: 10.1016/j.rser.2015.12.150.

[2] L. Stougie, N. Giustozzi, H. van der Kooi, and A. Stoppato, "Environmental, economic and exergetic sustainability assessment of power generation from fossil and renewable energy sources," *Int. J. Energy Res.*, vol. 42, no. 9, pp. 2916–2926, Jul. 2018, doi: 10.1002/er.4037.

[3] R. Kent, "Renewables," *Plastics Eng.*, vol. 74, no. 9, pp. 56–57, Oct. 2018, doi: 10.1002/peng.20026.

[4] Y. Kassem, H. Çamur, and R. A. F. Aateg, "Exploring solar and wind energy as a power generation source for solving the electricity crisis in Libya," *Energies*, vol. 13, no. 14, p. 3708, Jul. 2020.

[5] S. H. Saleh, "Forecasting of the electricity demand in Libya using time series stochastic method for long-term from 2011-2022," Sebelas Maret Univ., Surakarta, Indonesia, 2014.

[6] A. Khalil and A. Asheibe, "The chances and challenges for renewable energy in Libya," in *Proc. Renew. Energy Conf.*, Nov. 2015, pp. 1–6.

[7] A. M. A. Mohamed, A. Al-habaibeh, and H. Abdo, "Future prospects of the renewable energy sector in Libya," in *Proc. SBE*, Dubai, United Arab Emirates, Jan. 2016, p. 8. [Online]. Available: http://content.buid.ac.ae/events/Proceedings/SBE16D132.pdf

[8] I. M. S. I. Al-Jadi, M. A. EKhlat, and N. M. Krema, "Photovoltaic in Libya applications, and evaluation," in *Proc. Int. Conf. Renew. Energy Developing Countries*, Sep. 2005, pp. 1–11.

[9] J. Veleba and Z. Buhawa, "Perspectives of large wind power plant installations to the national transmission power system of Libya," *Gas*, vol. 4, no. 150, p. 600, 2011.

[10] A. M. A. Mohamed, A. Al-Habaibeh, H. Abdo, and M. J. R. Abdunnabi, "The significance of utilising renewable energy options into the Libyan energy mix," *Energy Res. J.*, vol. 4, no. 1, pp. 15–23, Jan. 2013, doi: 10.3844/erjsp.2013.15.23.

[11] C.-N. Wang, Y.-F. Huang, Y.-C. Chai, and V. Nguyen, "A multi-criteria decision making (MCDM) for renewable energy plants location selection in Vietnam under a fuzzy environment," *Appl. Sci.*, vol. 8, no. 11, p. 2069, Oct. 2018.

[12] J. Gao, H. Men, F. Guo, H. Liu, X. Li, and X. Huang, "A multi-criteria decision-making framework for compressed air energy storage power site selection based on the probabilistic language term sets and regret theory," *J. Energy Storage*, vol. 37, May 2021, Art. no. 102473, doi: 10.1016/j.est.2021.102473.

[13] C. Li, C. Xu, and X. Li, "A multi-criteria decision-making framework for site selection of distributed PV power stations along high-speed railway," *J. Cleaner Prod.*, vol. 277, Dec. 2020, Art. no. 124086, doi: 10.1016/j.jclepro.2020.124086.

[14] M. Abdel-Basset, A. Gamal, R. K. Chakrabortty, and M. Ryan, "A new hybrid multi-criteria decision-making approach for location selection of sustainable offshore wind energy stations: A case study," *J. Cleaner Prod.*, vol. 280, Jan. 2021, Art. no. 124462, doi: 10.1016/j.jclepro.2020.124462.

[15] H. H. H. Aly, "An intelligent hybrid model of neuro wavelet, time series and recurrent Kalman filter for wind speed forecasting," *Sustain. Energy Technol. Assessments*, vol. 41, Oct. 2020, Art. no. 100802, doi: 10.1016/j.seta.2020.100802.

[16] H. H. H. Aly, "A hybrid optimized model of adaptive neuro-fuzzy inference system, recurrent Kalman filter and neuro-wavelet for wind power forecasting driven by DFIG," *Energy*, vol. 239, Jan. 2022, Art. no. 122367, doi: 10.1016/j.energy.2021.122367.

[17] S. H. Mousavi-Nasab and A. Sotoudeh-Anvari, "A new multi-criteria decision making approach for sustainable material selection problem: A critical study on rank reversal problem," *J. Cleaner Prod.*, vol. 182, pp. 466–484, May 2018, doi: 10.1016/j.jclepro.2018.02.062.

[18] R. Joshi, "A new multi-criteria decision-making method based on intuitionistic fuzzy information and its application to fault detection in a machine," *J. Ambient Intell. Hum. Comput.*, vol. 11, no. 2, pp. 739–753, Feb. 2020, doi: 10.1007/s12652-019-01322-1.

[19] A. M. Rosso-Cerón, V. Kafarov, G. Latorre-Bayona, and R. Quijano-Hurtado, "A novel hybrid approach based on fuzzy multi-criteria decision-making tools for assessing sustainable alternatives of power generation in san Andrés island," *Renew. Sustain. Energy Rev.*, vol. 110, pp. 159–173, Aug. 2019, doi: 10.1016/j.rser.2019.04.053.

[20] E. Özcan, T. Danışan, R. Yumuşak, and T. Eren, "An artificial neural network model supported with multi criteria decision making approaches for maintenance planning in hydroelectric power plants," *Eksploatacja Niezawodność*, vol. 22, no. 3, pp. 400–418, Sep. 2020.

[21] R. Krishankumar, H. Garg, K. Arun, A. Saha, K. S. Ravichandran, and S. Kar, "An integrated decision-making COPRAS approach to probabilistic hesitant fuzzy set information," *Complex Intell. Syst.*, vol. 7, no. 5, pp. 2281–2298, Oct. 2021, doi: 10.1007/s40747-021-00387-w.

[22] S. Soltaniyan, M. R. Salehizadeh, A. Taşcıkaraoğlu, O. Erdinç, and J. P. S. Catalão, "An interactive multi-criteria decision-making framework between a renewable power plant planner and the independent system operator," *Sustain. Energy, Grids Netw.*, vol. 26, Jun. 2021, Art. no. 100447, doi: 10.1016/j.segan.2021.100447.

[23] T. Soha and B. Hartmann, "Complex power-to-gas plant site selection by multi-criteria decision-making and GIS," *Energy Convers. Manag. X*, vol. 13, Jan. 2022, Art. no. 100168, doi: 10.1016/j.ecmx.2021.100168.

[24] B. Wang, I. Nistor, T. Murty, and Y.-M. Wei, "Efficiency assessment of hydroelectric power plants in Canada: A multi criteria decision making approach," *Energy Econ.*, vol. 46, pp. 112–121, Nov. 2014, doi: 10.1016/j.eneco.2014.09.001.

[25] F. Ribeiro, P. Ferreira, and M. Araújo, "Evaluating future scenarios for the power generation sector using a multi-criteria decision analysis (MCDA) tool: The Portuguese case," *Energy*, vol. 52, pp. 126–136, Apr. 2013, doi: 10.1016/j.energy.2012.12.036.

[26] H. Zhao and N. Li, "Evaluating the performance of thermal power enterprises using sustainability balanced scorecard, fuzzy Delphic and hybrid multi-criteria decision making approaches for sustainability," *J. Cleaner Prod.*, vol. 108, pp. 569–582, Dec. 2015, doi: 10.1016/j.jclepro.2015.07.141.

[27] H. S. Dhiman and D. Deb, "Fuzzy TOPSIS and fuzzy COPRAS based multi-criteria decision making for hybrid wind farms," *Energy*, vol. 202, Jul. 2020, Art. no. 117755, doi: 10.1016/j.energy.2020.117755.

[28] S. S. Hosseini Dehshiri and S. J. Hosseini Dehshiri, "Locating wind farm for power and hydrogen production based on geographic information system and multi-criteria decision making method: An application," *Int. J. Hydrogen Energy*, vol. 47, no. 58, pp. 24569–24583, Jul. 2022, doi: 10.1016/j.ijhydene.2022.03.083.

[29] S. Feyzi, M. Khanmohammadi, N. Abedinzadeh, and M. Aalipour, "Multi-criteria decision analysis FANP based on GIS for siting municipal solid waste incineration power plant in the north of Iran," *Sustain. Cities Soc.*, vol. 47, May 2019, Art. no. 101513, doi: 10.1016/j.scs.2019.101513.

[30] B. Zlaugotne, L. Zihare, L. Balode, A. Kalnbalkite, A. Khabdullin, and D. Blumberga, "Multi-criteria decision analysis methods comparison," *Environ. Climate Technol.*, vol. 24, no. 1, pp. 454–471, Jan. 2020, doi: 10.2478/rtuect-2020-0028.

[31] C.-N. Wang, V. T. Nguyen, H. T. N. Thai, and D. H. Duong, "Multi-criteria decision making (MCDM) approaches for solar power plant location selection in Vietnam," *Energies*, vol. 11, no. 6, p. 1504, Jun. 2018, doi: 10.3390/en11061504.

[32] A. U. Rehman, M. H. Abidi, U. Umer, and Y. S. Usmani, "Multi-criteria decision-making approach for selecting wind energy power plant locations," *Sustainability*, vol. 11, no. 21, p. 6112, Nov. 2019, doi: 10.3390/su11216112.

[33] Y. Wu, F. He, J. Zhou, C. Wu, F. Liu, Y. Tao, and C. Xu, "Optimal site selection for distributed wind power coupled hydrogen storage project using a geographical information system based multi-criteria decision-making approach: A case in China," *J. Cleaner Prod.*, vol. 299, May 2021, Art. no. 126905, doi: 10.1016/j.jclepro.2021.126905.

[34] S. Zambrano-Asanza, J. Quiros-Tortos, and J. F. Franco, "Optimal site selection for photovoltaic power plants using a GIS-based multi-criteria decision making and spatial overlay with electric load," *Renew. Sustain. Energy Rev.*, vol. 143, Jun. 2021, Art. no. 110853, doi: 10.1016/j.rser.2021.110853.

[35] T. Ali, Y.-R. Chiu, K. Aghaloo, A. J. Nahian, and H. Ma, "Prioritizing the existing power generation technologies in Bangladesh's clean energy scheme using a hybrid multi-criteria decision making model," *J. Cleaner Prod.*, vol. 267, Sep. 2020, Art. no. 121901, doi: 10.1016/j.jclepro.2020.121901.

[36] H. H. H. Aly, "A novel deep learning intelligent clustered hybrid models for wind speed and power forecasting," *Energy*, vol. 213, Dec. 2020, Art. no. 118773, doi: 10.1016/j.energy.2020.118773.

[37] A. Rahmati and M. Sanaye-Pasand, "Protection of power transformer using multi criteria decision-making," *Int. J. Electr. Power Energy Syst.*, vol. 68, pp. 294–303, Jun. 2015, doi: 10.1016/j.ijepes.2014.12.073.

[38] B. G. Urošević and B. Marinović, "Ranking construction of small hydro power plants using multi-criteria decision analysis," *Renew. Energy*, vol. 172, pp. 1174–1183, Jul. 2021, doi: 10.1016/j.renene.2021.03.115.

[39] M. Ehteram, H. Karami, and S. Farzin, "Reservoir optimization for energy production using a new evolutionary algorithm based on multi-criteria decision-making models," *Water Resour. Manage.*, vol. 32, no. 7, pp. 2539–2560, May 2018, doi: 10.1007/s11269-018-1945-1.

[40] J. Waewsak, S. Ali, and Y. Gagnon, "Site suitability assessment of para rubberwood-based power plant in the southernmost provinces of Thailand based on a multi-criteria decision-making analysis," *Biomass Bioenergy*, vol. 137, Jun. 2020, Art. no. 105545, doi: 10.1016/j.biombioe.2020.105545.

[41] N. Bhushan and K. Rai, *Strategic Decision Making: Applying the Analytic Hierarchy Process* (Decision Engineering). London, U.K.: Springer, 2004, pp. 3–10.

[42] R. W. Saaty, "The analytic hierarchy process-what it is and how it is used," *Math. Model.*, vol. 9, nos. 3–5, pp. 161–176, 1987, doi: 10.1016/0270-0255(87)90473-8.

[43] H. Musbah, G. Ali, H. H. Aly, and T. A. Little, "Energy management using multi-criteria decision making and machine learning classification algorithms for intelligent system," *Electr. Power Syst. Res.*, vol. 203, Feb. 2022, Art. no. 107645, doi: 10.1016/j.epsr.2021.107645.

[44] S. Opricovic, "Multicriteria optimization of civil engineering systems," *Fac. Civil Eng., Belgrade*, vol. 2, no. 1, pp. 5–21, 1998.

[45] C.-L. Hwang and K. Yoon, "Methods for multiple attribute decision making," in *Multiple Attribute Decision Making: Methods and Applications*. Berlin, Germany: Springer, 1981, pp. 58–191.

[46] C.-T. Chen, "Extensions of the TOPSIS for group decision-making under fuzzy environment," *Fuzzy Sets Syst.*, vol. 114, no. 1, pp. 1–9, Aug. 2000.

[47] E. K. Zavadskas, A. Kaklauskas, and V. Šarka, "The new method of multicriteria complex proportional assessment of projects," *Technol. Econ. Develop. Econ.*, vol. 1, no. 3, pp. 131–139, 1994.

[48] G. Ali, H. H. Aly, and T. Little, "Using Homer software to investigate, size and apply renewable energy sources in a convention center in Sabratha, Libya," in *Proc. Int. Conf. Electr., Commun., Comput. Eng. (ICECCE)*, Jun. 2021, pp. 12–13, doi: 10.1109/ICECCE52056.2021.9514156.

[49] G. Ali and M. El-Hawary, "Generating heat and power from biomass—An overview," in *Proc. IEEE Can. Conf. Electr. Comput. Eng. (CCECE)*, May 2019, pp. 1–6, doi: 10.1109/CCECE43985.2019.9052399.

[50] T. L. Saaty, *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*. New York, NY, USA: McGraw-Hill, 1980, p. 21.

GAMA ALI (Student Member, IEEE) received the M.Eng. degree in electrical engineering from Lausitz University, Germany, in 2005. He is currently pursuing the Ph.D. degree with the Department of Electrical and Computer Engineering, Dalhousie University, Canada. He has more than 13 years of teaching and research experience and has published papers in IEEE conferences and journals. His research interests include distributed generation, green energy, optimization, power transmission and distribution, power quality management, and smart grids.

HMEDA N. MUSBAH (Student Member, IEEE) received the M.A.Sc. degree in automation engineering from Tripoli University, Libya, in 2009. He is currently pursuing the Ph.D. degree in electrical and computer engineering with Dalhousie University, Canada. He has more than 13 years of teaching and research experience and has published papers in IEEE conferences and journals. His research interests include smart grids, distributed generation, applications of artificial intelligence in power systems, and energy management applications.

HAMED H. ALY (Senior Member, IEEE) received the B.Eng. and M.A.Sc. degrees (Hons.) in electrical engineering from Zagazig University, Egypt, in 1999 and 2005, respectively, and the Ph.D. degree from Dalhousie University, Canada, in 2012. For one year, he was a Postdoctoral Research Associate with Dalhousie University, where he was an Instructor for three years. He was also an Assistant Professor with Acadia University for three years. He is currently an Assistant Professor with Dalhousie University. His research interests include micro grids, smart grids, distributed generation, power quality issues, applications of artificial intelligence in power systems, energy management, green energy, and optimization.

TIMOTHY LITTLE is currently the Associate Dean of the Faculty of Engineering and a full-time Associate Professor with the Department of Electrical and Computer Engineering, Dalhousie University, Canada. His research interests include engineering education, wind energy and renewable generation, power electronics, and electromechanical energy conversion.