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Using Grey-TOPSIS approach for solar farm location selection in Libya

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ABSTRACT

The utilisation of renewable energies has emerged as a pressing environmental imperative, particularly in view of the elevated levels of pollution and amplified global warming resulting from the consumption of vast quantities of fossil fuels for energy generation. The field of research has contributed to the reduction of expenses associated with the acquisition of renewable energy, thereby positioning it as a formidable contender against conventional energy sources. Although several developed nations have made significant progress in integrating renewable energy sources into their energy portfolio, developing countries still face challenges in this regard, despite the accessibility of such energy sources. The present investigation employed a hybrid multi-criteria approach that integrates the GREY-TOPSIS method to identify the optimal location for the establishment of a solar farm. A total of twelve criteria were utilised to evaluate and contrast the suggested locations. The GREY method was employed for the purpose of extracting criteria weights. A comparative analysis was conducted on six potential locations within the Libyan territory, considering a set of twelve established criteria. It is noteworthy that Libya's energy generation is predominantly reliant on non-renewable sources. According to the findings, the criteria of average solar radiation and sunshine hours hold the highest significance with a weightage of 0.9. As per the model, Misrata emerged as the highest-ranking city with a weightage of 0.53, while Benghazi, situated in the western region of the country, secured the second position with a value of 0.47. The methodology and evaluation criteria utilised in this study have the potential to be implemented in other urban areas, thereby facilitating the pursuit of sustainable development.

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1. Introduction

Governments across the globe are placing considerable emphasis on the delivery of clean energy services. Governments are implementing policies and action plans to attain the decarbonization of electricity systems by means of the extensive integration of renewable generation. The European Commission has established a goal for renewable energy sources to account for a minimum of 32% of the overall energy demand in the European Union (EU) by the year 2030. As a result of these aforementioned policies, there has been a substantial growth in the solar energy sector on a global scale over the past decade. According to a source (Oderinwale & McInnes, 2022), the global cumulative solar PV installation witnessed a 31-fold increase in capacity by the conclusion of 2018 in comparison to the figures recorded in 2008. According to projections, the total worldwide capacity for photovoltaic installations is expected to reach approximately 1296 GW by the conclusion of 2023. This represents a significant increase in capacity of 81 times the amount recorded in 2008 (Oderinwale & McInnes, 2022).

Numerous nations across the globe have been engaged in the endeavour of transitioning their energy systems for several decades, with the aim of mitigating climate change (Razeghi et al., 2023). Renewable energy sources have emerged as a significant alternative for sustainable energy, offering numerous environmental benefits. As per the Paris Agreement of 2015, which was ratified by 193 nations, the shared objective is to restrict the increase in global temperature to a maximum of 2°C, and preferably to 1.5°C, in comparison to the pre-industrial era. The primary objective at the European level is to attain climate neutrality by the year 2050 (Vrînceanu et al., 2022). The approach to transition towards a contemporary, competitive, and resource-efficient economy is outlined in the European Green agreement.

In the past few years, there has been a proliferation of research studies on solar energy, examining various aspects including costs and technologies, as well as policy implications and environmental impact (Shao et al., 2020). The overarching objective of these studies is to optimise performance while minimising negative impacts on the environment, social and cultural infrastructure, and administrative and authorization procedures. Several spatial analysis techniques have been utilised to determine and simulate the most suitable locations for photovoltaic farms at a continental, national, or regional level. Multi-Criteria Decision-Making approaches are a commonly utilised technique for assessing the potential of solar farms. These methods are often integrated into Geographic Information System (GIS) spatial analysis and have been extensively employed in various recent studies (Badi et al., 2021; Ruiz et al., 2020). The aim of this research is to identify the optimal site for the establishment of a solar farm in Libya.

2. Current situation of energy in Libya

Libya is located in the high sun belt and has a long coastline on the Mediterranean Sea, which makes it one of the countries with very high potential for solar and wind energy. Despite the abundance of these valuable renewable resources, their contribution to energy production remains minimal and, although they are endowed with enormous renewable energy resources, the share of renewables in electricity production is negligible. Libya is currently totally dependent on oil and natural gas to generate electricity (Pamučar et al., 2018). Libya is currently totally dependent on oil and natural gas to generate electricity. Both of these traditional resources are limited and depleted, resulting in increased carbon dioxide emissions. Due to inadequate planning, some renewable energy projects are delayed or suspended, and the lack of data makes planning and decision making difficult. There are no good surveys or detailed studies on the current energy situation and changing needs in Libya (Badi et al., 2023).

2.1 Why Solar Energy in Libya?

According to the Libyan Bureau of Statistics and Census, Libya's population reached 6.93 million (million) in 2020 with a growth rate of 1.96%. The population density of this Mediterranean country is unevenly distributed over an area of 1.76 square meters, ranging from 300 inhabitants/km2 in the northern coastal areas to less than 1 inhabitant/km2 in the south of the country which is characterized by a harsh desert environment (Badi et al., 2021). The oil sector is the main driver of the Libyan economy, accounting for about 95 percent of export revenues and 65 percent of GDP. Oil export revenues amounted to $24 billion and $22 billion in 2018 and 2019, respectively (Pamučar et al., 2018; Tanackov et al., 2022). With its small population and large energy sector revenues, Libya has one of the highest gross incomes per capita in Africa. Unfortunately, political instability has severely affected the development of the energy sector and recently led to the closure of the main oil fields in January 2020.

2.2 Electricity Power Status

To date, the Libyan electricity market is fully regulated by the General Electricity Company Libya (GECOL). This state-owned company has a monopoly on the production, transmission and distribution of electricity. According to the General Electricity Company, the average daily gas supply needed to generate electricity in 2019 was 581 million cubic feet (MCF), which represents 26.7 percent of the national daily gas production. Natural gas accounts for about 63% of Libya's electricity (Pamučar et al., 2018; GECOL, 2013).

Approximately 29% of Libya's electricity is generated by oil-fired power plants, while the remainder comes from shared non-fuel steam power plants. Around 29% of Libya's electricity is generated by oil-fired power plants, while the remainder comes from shared non-fuel steam plants. By type of generation, fuel-fired plants account for 39.3% of total electricity production, while combined cycle and steam technology account for 48.2% and 10.6% respectively. The remainder is covered by small gas-fired units (GECOL, 2013).

As a result of rising demand, an outdated transmission system, lack of routine maintenance and massive damage to the power grid infrastructure, electricity production has always been lower than demand, leading to regular power cuts (Ahmed, 2019). It is undeniable that Libya's fossil resources, at the current rate of production and use, will be exhausted within a century or even a few decades. What's more, the price of oil is set to rise to over $200 a barrel by 2050, in response to strong demand (Pamučar et al., 2018). At that time, Libya will be faced with a dilemma: choosing between selling its oil or using it to generate electricity (Alfagi, 2021).

Consequently, precautionary measures should be taken to diversify energy resources and maintain the viability of future generations. Renewable energies are undoubtedly the key to meeting the growing demand for clean, sustainable energy.

3. Methodology

Multi-criteria decision making (MCDM) is a process of selecting the best option among a set of alternatives based on multiple criteria or objectives. It involves evaluating each alternative against a set of criteria and determining the relative importance of each criterion (Stević et. al., 2022; Więckowski et. al., 2023). MCDM is widely used in various fields, including engineering, economics, and management, to support decision-making processes that involve complex and conflicting objectives (Tripathi et al., 2023). The utilisation of Multiple Criteria Decision Making (MCDM) is a common technique employed by researchers to facilitate decision-making processes that involve prioritisation, classification, or selection of preferences. The MCDM approach is designed to account for preferences across multiple criteria and their associated effects, whether they are quantitative, qualitative, or conflicting in nature, in order to reach a consensus (Alosta et al., 2021). Multiple fields of study, such as information systems, economics, computer science, and behavioural decision theory, are employed. Various Multi-Criteria Decision Making (MCDM) methodologies have been efficaciously employed in diverse domains of necessity (Božanić et al., 2020; Bouraima et al., 2023a).

Various Multiple Criteria Decision Making (MCDM) techniques exist, including but not limited to the Analytical Heirarchy Process, Fuzzy Decision Making, and Data Envelopment Analysis. Despite the widespread application of these techniques in various studies, Multiple Criteria Decision Making (MCDM) remains a rapidly expanding area of concern across numerous research domains. All approaches possess equivalent decision-making capabilities in situations where trust is deficient, and each approach has its unique set of benefits (Bouraima et al., 2023b, 2023c).

In 1982, Deng presented grey system theory as a mathematical methodology for the first time. The theory has demonstrated successful application in addressing modelling challenges that arise from limited data and incorporating uncertainty into complex systems. The grey theory is a modelling approach that is specifically designed to analyse systems with limited information, in contrast to conventional methods that typically require a substantial number of samples. The grey system theory has been efficiently employed in diverse research domains, such as finance, engineering, social science, and economics. In the context of information systems, the term "white" is used to denote a state in which all relevant information is available, whereas the term "black" is used to denote a state in which all relevant information is unavailable. The term "grey system" is used to describe situations where there is incomplete information (Badi & Pamucar, 2020).

The concept of grey number pertains to a quantifiable metric in which the precise value is unknown, and only the range of potential values is ascertainable. The symbol ⊗ is utilised to denote the unknown parameters of the grey system, which can be either discrete or continuous grey numbers. The theoretical framework encompasses several attributes and procedures pertaining to grey numbers, such as the core of the number ⊗, its degree of greyness denoted as g°, and the degree of whitening of the grey number, which characterises the tendency of a number to be situated in the centre of a range of feasible values.

The present study employs a hybrid approach that integrates the Grey theory and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method to facilitate the decision-making process for identifying the optimal location for establishing a solar farm in Libya. The objective of this study is to execute the hybrid approach for ranking the six suggested locations. The determination of priority weights for various sites was conducted through the utilisation of MS Excel macros. This process involved the use of questionnaire forms to compare the criteria and proposed sites.

The Grey-TOPSIS model is conducted on eight steps as follows (Gergin et al., 2022; Cakar & Çavuş, 2021):

Step 1: The process of identifying a solar farm location involves selecting a set of critical attributes or criteria that are deemed most significant for this purpose.

Step 2: Using the following equations to calculate the weight of attributes W_j:

$$\otimes W_j = \frac{1}{K}\left[\otimes W_j^1 + \otimes W_j^2 + \cdots + \otimes W_j^K\right] \tag{1}$$

$$\otimes W_j^K = \left[\underline{W}_j^K, \underline{W}_j^K\right] \tag{2}$$

Step 3: The evaluation of alternatives is conducted by experts who provide their professional assessment based on linguistic or verbal criteria.

$\otimes G_{ij}^{K}, (i = 1,2,\dots,m; j = 1,2,\dots,n)$is the value of the attribute obtained from the kth expert to any of the alternatives which is represented as, $\otimes G_{ij}^{K} = \left[\underline{G}_{ij}^{K}, \overline{G}_{ij}^{K}\right]$ and calculated using the following formula:$\otimes G_j = \frac{1}{K}\left[\otimes G_j^1 + \otimes G_j^2 + \cdots + \otimes G_j^K\right]$

Step 4: Forming the Grey Decision Matrix:

$$G = \begin{bmatrix} \otimes G_{11} & \otimes G_{12} & \cdots & \cdots & \otimes G_{1n} \\ \otimes G_{21} & \otimes G_{22} & \cdots & \cdots & \otimes G_{2n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \\ \otimes G_{m1} & \otimes G_{m2} & \cdots & \cdots & \otimes G_{mn} \end{bmatrix} \tag{3}$$

Calculate the weighted normalized decision matrix.

$$V = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & w_3 r_{13} & \dots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & w_3 r_{23} & \dots & w_n r_{2n} \\ . & & & & . \\ . & & & & . \\ . & & & & . \\ w_1 r_{m1} & w_2 r_{m2} & w_3 r_{m3} & \dots & w_n r_{mn} \end{bmatrix}$$

Step 5: Determine the positive ideal and negative ideal solution from the matrix A.

$$A^{+} = \left\{ \left(\max v_{ij} \,\middle|\, j \in J\right), \left\{ \left(\min v_{ij} \,\middle|\, j \in J^{I}\right), i = 1,2,3,\dots\dots\dots m \right\}\right.$$

$$= \{ v_{1^*}, v_{2^*}, \dots\dots. v_{n^*} \} \tag{3 − 3}$$

$$A^{-} = \left\{ \left(\min v_{ij} \,\middle|\, j \in J\right), \left\{ \left(\max v_{ij} \,\middle|\, j \in J^{I}\right), i = 1,2,3,\dots\dots\dots m \right\}\right.$$

$$= \{ v_{1-}, v_{2-}, \dots\dots. v_{n-} \} \tag{4}$$

Step 6: Calculate the separation measures, using the n-dimensional Euclidean distance. The separation of each alternative from the positive ideal solution is given as

$$S_{i_*} = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_{j*})^2 \quad , for \ i = 1, \ 2, \ 3, \dots\dots, m} \tag{5}$$

$$S_{i\_} = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_{j-})^2 \quad , for \ i = 1, \ 2, \ 3, \dots\dots, m} \tag{6}$$

Step 7: For each alternative, calculate the ratio Ri as

$$c_{i*} = \frac{s_{i-}}{s_{i+} + s_{i-}} \tag{7}$$

Step 8: Rank alternatives in increasing order according to the ratio value of Ri in step 5.

4. Results and discussion

Figure 1 shows the model used in this study to select the most suitable site for a proposed solar farm with a capacity of (500 MW). 12 criteria and 6 alternatives were selected for comparison. The model includes the selection and evaluation of the criteria, followed by the evaluation of the alternatives.

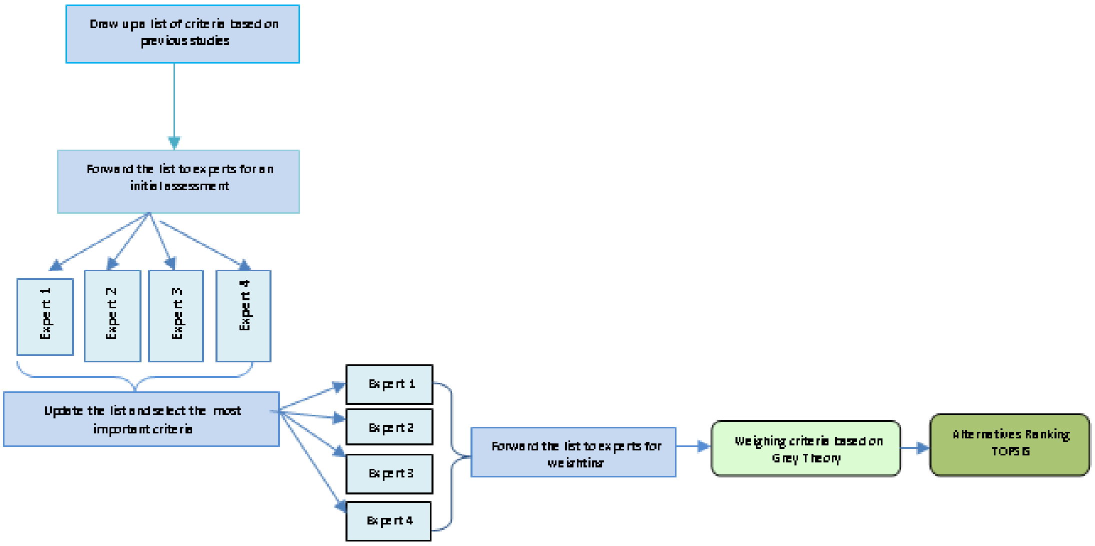

Figure 1. Proposed model

This study was carried out in six Libyan cities spread across the south, east, west and center of Libya, namely Misrata, Benghazi, Tripoli, Tobruk, Sabha, and Kufra. Twelve criteria for comparing these cities were developed with the aim of selecting one of them as the best city to set up a solar farm in Libya. **Table** 1 shows the criteria according to which the six selected cities were compared. The criteria were selected on the basis of previous studies and then submitted to a panel of experts tasked with evaluating the criteria and adding those they deemed important.

Table 1. Criteria selected in the research

No.	Title	Description
C1	Average Solar Radiation	Amount of solar radiation incident on a given area and capable of producing electrical energy
C2	Wind Speed	Air currents that move rapidly from one side of the Earth's surface to the other
C3	Ease of Project Construction	Ease of equipment access to the project site
C4	Sunshine Hours	A climate indicator that measures the duration of the sun's brightness over a given period for a specific site
C5	Ambient Temperature	Average temperature in and around the project area
C6	Large Areas Targeted for Construction	Large areas are needed to build the project
C7	Ease of Distribution of Produced Energy	Proximity of the project site to electrical power distribution networks and to the consumer
C8	Proximity of the Project Area to the Coast and Possibility of Exporting to Europe	Proximity of the Project Area to the Libyan Coast and Europe

No.	Title	Description
C9	Provision of Human Resources Close to the Project Area	Human resourses availability
C10	Topography of the Region	Project is not built in mountains and valleys
C11	Ensuring the Security of the Project Area During and After the Construction Process	Building the project in an area that can be protected against theft and destruction
C12	Providing Information	Provision of data and information about the region relevant to achieving the project

Figure 2 shows the potential alternatives (cities) considered in this research.

Figure 2. Potential cities considered in this research

The evaluation forms were distributed to four experts in the field of solar energy, and the data obtained was collected and the arithmetic mean was taken. After the collection process, the data is processed in the form of the decision matrix. Once the decision matrix has been obtained, the weights of the criteria are calculated to determine the importance or impact of each criterion in the selection process: Grey Theory for determining the weights of these criteria. **Table** 2 shows the experts' assessment of the criteria set out in the questionnaire.

Table 2. The linguistic assessment of the attributes by experts.

Ci	**Expert #1**	**Expert #2**	**Expert #3**	**Expert #4**	**Weight**
C1	VH	VH	VH	VH	0.900
C2	H	H	M	H	0.638
C3	M	M	H	H	0.575
C4	VH	VH	VH	VH	0.900
C5	H	H	H	H	0.700
C6	H	H	VH	H	0.750
C7	H	H	H	H	0.700
C8	M	M	H	H	0.575
C9	M	H	H	H	0.638
C10	H	H	H	VH	0.750
C11	H	H	VH	VH	0.800
C12	VH	VH	H	H	0.800

Using Grey Theory to determine the weight of each criterion, the standard values of the evaluations obtained were calculated. **Table** 3 shows Standard Grey Theory values corresponding to the evaluations obtained.

Table 3. The importance of grey number for the weights of the criteria.

Importance	**Abbreviation**	**Scale of grey number** $\otimes \boldsymbol{W}$
Very Low	VL	[0.0, 0.1]
Low	L	[0.1, 0.3]
Medium Low	ML	[0.3, 0.4]
Medium	M	[0.4, 0.5]
Medium High	MH	[0.5, 0.6]
High	H	[0.6, 0.8]
Very High	VH	[0.8, 1.0]

After the data conversion process, the data are placed in the form of a matrix with the columns corresponding to the experts and the rows corresponding to the alternatives to find out their weight. The average minimum and maximum values for each alternative are then calculated, followed by the average of the minimum and maximum values. **Table** 2 shows the final weighting for each criterion.

Table 4 shows how the criteria were evaluated, the scale used from 1 to 100 for some criteria and the rest of the criteria were calculated by programs prepared for this purpose to evaluate the cities according to each criterion, the weight of each criterion being determined by the entropy theory model (GREY theory).

Table 4. The criteria evaluation method used

Ci	**Calculation method**
C1	Calculated by the GLOBAL SOLAR ATLAAS SOFTWARE
C2	Calculated by the PVSYST SOFTWARE
C3	Weighed based on expert opinion
C4	Calculated by the Weather Atlas Softwear
C5	Calculated by the PVSYST SOFTWARE
C6	Weighed based on expert opinion
C7	Weighed based on expert opinion
C8	Calculated by Google Earth Softwear
C9	Weighed based on expert opinion
C10	Weighed based on expert opinion
C11	Weighed based on expert opinion
C12	Weighed based on expert opinion

Table 5 shows the values obtained from the experts' opininos and by calculations, as mentioned in **Table** 4.

Table 5. Values obtained for different cities

Ci	**Misrata**	**Sabha**	**Tobruk**	**Tripoli**	**Benghazi**	**Kufra**
C1	2213	2496	2215	2154	2215	2566
C2	4.3	5.2	4.7	3.7	4	5.2
C3	87.5	63.75	70	82.5	68.75	57.5
C4	8.6	10	8.833	8.75	8.675	9.975
C5	21	24.2	19.3	21	21.8	24.2
C6	79.25	93.75	77.5	68.75	77.5	93.75
C7	87.5	80.25	68.75	90.5	82.75	60.5
C8	450	1075	970	455	685	1600
C9	93.75	70	73.75	91.25	86.75	58.75
C10	87.5	85	80	82	85	77.5
C11	93.75	35	75	75	63	33
C12	91.75	73.75	78.75	91	83	63.75

A TOPSIS model was prepared with a decision matrix containing six rows (n=6) representing the alternatives, and twelve columns (m=12) representing the criteria. Table 6 shows the evaluations obtained from the questionnaire, with the scale used (from 1 to 100) to evaluate these cities according to each criterion.

Calculate the relative proximity of the ideal solution $\mathbf{c_{i*}}$ using eq. (7)

$$\mathbf{C_{1*}} = \frac{\mathbf{0.65325}}{\mathbf{0.65325 + 0.57206}} = \mathbf{0.53313}$$

After calculating the relative proximity, we rank the alternatives according to preference, the alternative with the highest relative proximity being the best and the alternative with the lowest relative proximity being the worst; **Table** 6 shows the alternatives' ranking.

Table 6. Ranking of alternaives

Alternative	Si+	Si-	Ci+	Ranking
Misrata	0.57206	0.65325	0.53313	1
Sabha	0.55191	0.43778	0.44234	4
Tobruk	0.55370	0.49712	0.47308	2
Tripoli	0.76714	0.60518	0.44099	5
Benghazi	0.57244	0.51355	0.47289	3
Kufra	0.84471	0.39058	0.31619	6

In this research, the objective was to select the best area in Libya to establish a solar farm project with a capacity of 500 MW. For this purpose, six cities were compared according to twelve criteria using multi-criteria methods. Analysis of the Grey Theory revealed that the criterion with the greatest impact on the process of selecting the best city to establish a solar farm is average solar radiation and sunshine hours with a weight of (0.9), i.e. cities with high average irradiance and high hours of sunshine are the most likely to become cities for establishing solar farms, taking into account the rest of the criteria and their weights. The criteria providing information on the process and previous studies and ensuring the security of the project area during and after the construction process come in second place with a weighting of (0.8). In third place were the criteria surface area allocated for construction and the criterion geography of the city and its distance from the mountains and valleys with a weight of (0.75). **Figure** 3 shows the criteria weights.

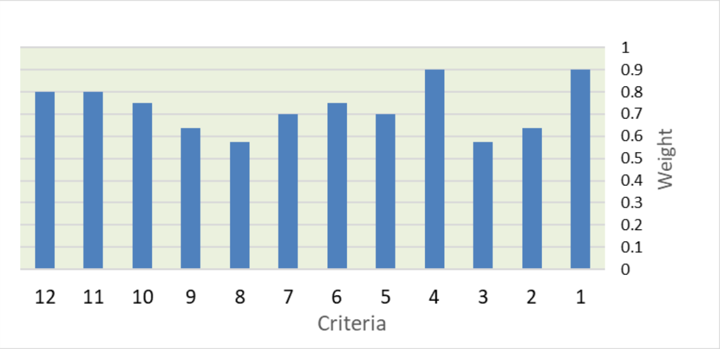

Figure 3. Criteria Weights

Using TOPSIS method to rank the alternatives, we first note that Misrata is the best city to establish a solar farm with the highest relative proximity to the ideal solution (0.53313). This is due to the fact that most of the criteria have the highest score, although it does not have the highest average radiance nor does it have the maximum number of sunshine hours, but it is very close to the highest value. Benghazi came second (0.47474), characterised by low temperatures and low wind speed. The city of Tobruk came third with relative proximity to the ideal solution (0.47280). The city of Tripoli ranked fourth with a relative proximity (0.44278), due to the lowest value for average solar radiation and a poor assessment of the areas required for construction, despite having the lowest wind speed of the six cities included in the comparison. The city of Sabha came fifth for its relative proximity to the ideal solution (0.44241), although it has the highest number of sunshine hours and the second highest value for average radiation, but it has the highest temperature and a low rating in terms of the project's ease of construction, as well as security. The city of Kufra comes at the end of the ranking, with a relative proximity to the ideal solution (0.31619). This can be explained by the fact that it is poorly rated in terms of providing security, which most cities in southern Libya suffer from. The city of Kufra also suffers from high temperatures, which negatively affects the work of high-efficiency panels. **Figure** 4 shows the ranking of the alternatives using the criteria weights by means of TOPSIS method.

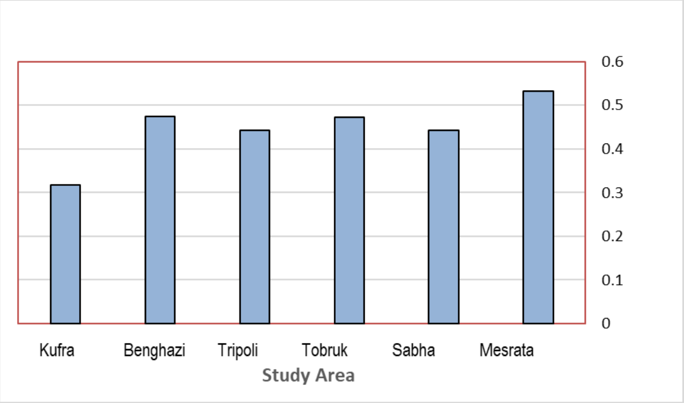

Figure 4. Alternatives ranking

5. Conclusion

Libya encompasses a landmass of approximately 1.8 million square kilometres. The extensive expanse of this region, coupled with its geographic location, renders it abundant in sources of renewable energy. Regrettably, Libya remains incapable of harnessing these resources due to various factors, with the foremost being the presence of vast reserves of fossil fuels in the country. Undoubtedly, this resulted in the deferral of pivotal investment decisions in such projects. The occurrence of frequent power outages and the ageing of current power plants are likely to prompt considerations regarding investment in renewable energy sources. Among these, solar energy is arguably the most significant. The process of identifying appropriate locations for constructing solar energy farms is a critical and intricate aspect of investment in this sector. The decision-making process involves numerous criteria, and their effects are contingent upon the specific country in question. Consequently, it is imperative that such decisions receive meticulous scrutiny. The present research endeavours to establish a foundation for the criteria that ought to be considered when arriving at this determination. The research conducted a comparative analysis of six distinct urban areas. The selection of these cities was based on prior research and the opinion of experts. The comparative analysis was conducted based on a set of 12 distinct criteria. The present study offers a valuable tool for decision-makers to facilitate informed decision-making regarding optimal locations for the establishment of solar farms.

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