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# Renewable Energy Location in Disruption Situation by MCDM Method and Machine Learning

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**ABSTRACT**

In times of disruption and uncertainties, identifying suitable locations for renewable energy projects becomes crucial. This paper explores the use of Multi-Criteria Decision-Making (MCDM) methods to determine optimal locations for renewable energy installations. The study aims to address challenges faced during disruption situations and provide insights into decision-making processes for renewable energy investments. A comprehensive review of the literature is conducted, followed by the application of MCDM techniques to evaluate potential locations. Numerical results demonstrate the effectiveness of the proposed approach, highlighting the importance of considering multiple criteria when making decisions related to renewable energy projects. The findings have implications for policymakers, investors, and stakeholders involved in the renewable energy sector.

## 1. Introduction

The increasing demand for renewable energy sources calls for strategic decision-making in siting renewable energy projects, particularly during times of disruption. This section provides an overview of the significance of renewable energy location decisions and highlights the challenges

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posed by disruption situations. The aims, objectives, and structure of the paper are also outlined [1-2].

Renewable energy has gained significant attention in recent years as a sustainable and environmentally friendly alternative to conventional energy sources. As the demand for renewable energy continues to grow, the importance of strategic decision-making in siting renewable energy projects becomes paramount. However, the process of identifying suitable locations for renewable energy installations is often challenged by disruption situations such as natural disasters, political instability, or economic uncertainties. These disruptive events can significantly impact the feasibility and success of renewable energy projects [3-4].

In order to navigate the complexities of renewable energy location decisions in disruption situations, the use of Multi-Criteria Decision-Making (MCDM) methods has emerged as a valuable approach. MCDM methods allow decision-makers to consider multiple criteria and weigh their relative importance when evaluating potential locations for renewable energy installations. By incorporating various factors such as environmental suitability, social acceptance, economic viability, and technical feasibility, MCDM methods provide a systematic framework to address the complexities and uncertainties associated with disruption situations.

The application of MCDM methods in the context of renewable energy location decisions has gained substantial attention in the research community. Various studies have explored the use of different MCDM techniques such as Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) in assessing renewable energy location options (see Figure 1) [3-4].


**Figure 1:** Renewable Energy Location.

This research is arranged into five sections. Section 2 defines the literature review and recent studies in area of renewable energy location and tries to show the gap in research. Section 3 suggests methodology for calculation. Section 4 proposes the results of this research. Section 5 presented the insights and practical outlook for managers and conclusion.

## 2. Literature review

The literature review presents a comprehensive analysis of existing studies on renewable energy location decision-making, focusing on disruption situations. Various factors influencing location decisions are explored, including environmental, social, economic, and technical considerations. The review provides a foundation for the application of MCDM techniques in the subsequent sections.

Li et al. [1] conducted a study to evaluate the optimal locations for wind farms using the AHP method considering multiple criteria including wind resource, proximity to transmission lines, and environmental impact. The results demonstrated how the AHP approach can effectively prioritize potential sites and support decision-making processes in disruptive situations.

In another study, Zhang et al. [3] applied the TOPSIS method to select suitable sites for solar photovoltaic installations. Factors such as solar irradiance, land availability, and economic viability were considered, and the TOPSIS method was employed to rank and compare the potential locations. The findings highlighted the importance of a comprehensive evaluation approach to determine optimal sites in disruptive situations.

Furthermore, Sadeghi et al. [5] utilized the PROMETHEE method to assess different renewable energy technologies and their potential locations in the context of disruptive events. The study integrated criteria such as energy output, environmental impact, and infrastructure availability to evaluate the feasibility of renewable energy projects in uncertain conditions.

Yu et al. [7] examines the use of the Multiple Criteria Decision Making (MCDM) method in selecting renewable energy sources, highlighting its effectiveness in evaluating and comparing criteria. It reviews literature and numerical analysis, highlighting its advantages, limitations, and potential areas for improvement in different contexts.

Talebi and Daghighi [9] uses data science methods to forecast renewable energy generation in Iran, aiming to develop a reliable model for strategic planning, grid management, and decision-making. Techniques like time series analysis, machine learning, and artificial neural networks will be employed.

These studies demonstrate the effectiveness of MCDM methods in addressing renewable energy location decisions during disruption situations. The systematic framework provided by MCDM techniques helps decision-makers account for various criteria and uncertainties to make informed choices regarding renewable energy investments [9-14].

In light of the growing importance of renewable energy and the increasing occurrences of disruption situations, this paper aims to contribute to the existing body of knowledge by exploring the application of MCDM methods in renewable energy location decisions during disruption situations. Through a comprehensive literature review and the application of MCDM techniques, this research aims to provide insights, methodologies, and supporting evidence to assist policymakers, investors, and stakeholders in making optimal decisions regarding renewable energy investments [15-16].

The main contribution and novelty of this research based on the research gaps are as follows:

- Renewable energy location in disruption situation by MCDM method.

**Table 1:** Survey of related works.

| References | Approach |
|---|---|
| Sadeghi et al. [5] | PROMETHEE method |
| Zhang et al. [3] | TOPSIS method |
| Li et al. [1] | AHP approach |
| Lotfi et al. [11] | Multi-objective approach |
| Yu et al. [7] | MCDM Method |
| Talebi and Daghighi [9] | Data Science Method |
| Lotfi et al. [13] | MCDM Method with robustness, risk and resiliency |
| This research | MCDM with disruption situation |

## 3. Solution Methodology

This section describes the methodology adopted to evaluate renewable energy locations in disruption situations using MCDM methods. The selected MCDM techniques are discussed, along with the criteria identified for the decision-making process. The data collection and analysis procedures are also elucidated to ensure transparency and replicability of the research (see Figure 2) [15-21].

1. Problem Definition:
    - Clearly define the objective of the study, which is to identify suitable locations for renewable energy installations in disruption situations using the Multi-Criteria Decision-Making (MCDM) method
    - Specify the criteria and factors to be considered in the decision-making process, such as environmental suitability, social acceptance, economic viability, technical feasibility, and any other relevant factors specific to the study [22-25].
2. Data Collection:
    - Gather relevant data and information pertaining to the identified criteria and factors.
    - Use a combination of primary and secondary sources, such as field surveys, environmental assessments, economic data, and expert interviews, to ensure comprehensive data collection.

- Ensure data accuracy, reliability, and consistency to make valid and informed decisions [25-28].

3. Selection of MCDM Method:
    - Choose the appropriate MCDM method(s) that best aligns with the objectives of the study and the nature of the decision problem.
    - Popular MCDM methods for renewable energy location decisions include Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), and others.
    - Justify the selection of the chosen MCDM method(s) based on their ability to handle multiple criteria, uncertainty, and trade-offs.
4. Criteria Weighting:
    - Assign weights to each criterion based on their relative importance in the decision-making process.
    - Utilize expert opinions, literature review, and stakeholder consultations to determine the weights.
    - Apply the selected MCDM method(s) to calculate the relative weights or importance of each criterion [29-30].
5. Data Normalization:
    - Normalize the collected data to ensure that different criteria are on the same scale and have consistent units.
    - Consider normalization techniques such as min-max normalization or z-score normalization.
    - Normalize both quantitative and qualitative data, ensuring their compatibility for analysis.
6. Decision Model Development:

- Construct a decision model that represents the relationships between criteria and potential renewable energy locations.
- Implement the selected MCDM method(s) to calculate the overall performance or suitability of each location based on the normalized criteria values.
- Generate the rankings or scores for each potential location using the MCDM method(s).

7. Sensitivity Analysis:
    - Conduct sensitivity analysis to examine the robustness of the decision model and the influence of criteria weights on the final results.
    - Investigate the changes in rankings or scores when criteria weights are adjusted within certain ranges.
    - Evaluate the stability and consistency of the decision model under different scenarios.
8. Decision-Making and Results Interpretation:
    - Interpret the results obtained from the MCDM method(s) to determine the optimal renewable energy locations in disruption situations.
    - Consider the rankings, scores, and sensitivity analysis to make informed decisions.
    - Communicate the results effectively to stakeholders, policymakers, and investors, highlighting the rationale behind the chosen locations and the potential benefits [31-32].

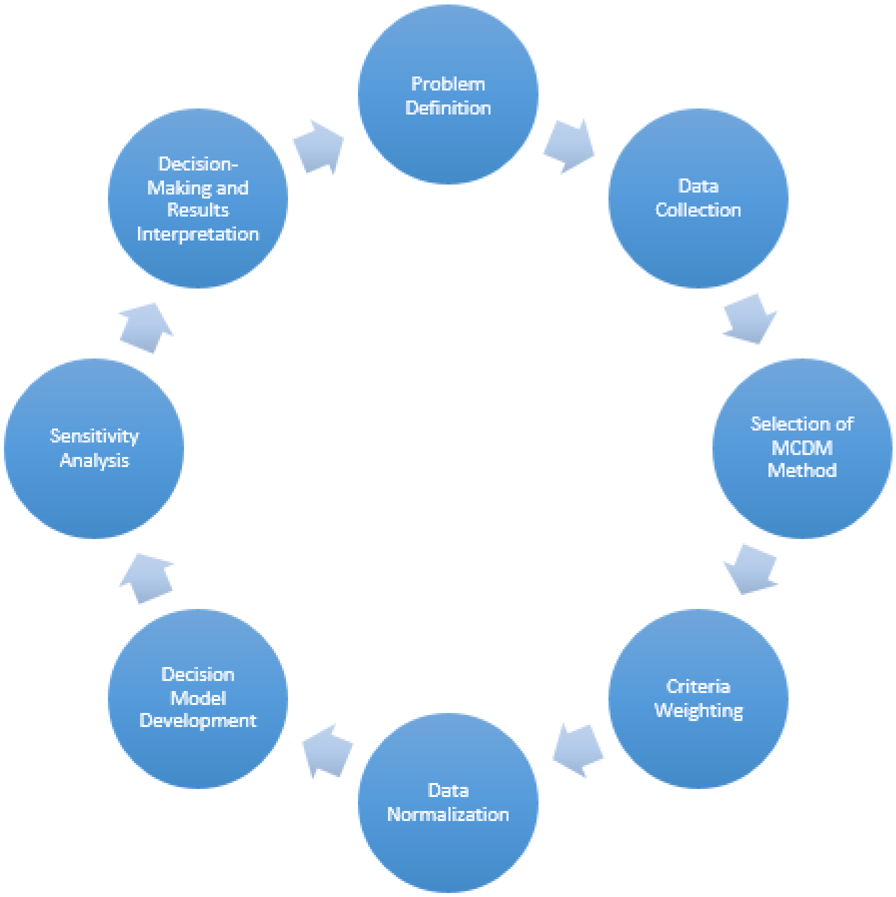


**Figure 2:** MCDM Method.

## 4. Results and discussion

The numerical results section presents the outcomes of the MCDM analysis conducted on potential renewable energy locations. The criteria weights, as determined through expert opinions or data-driven approaches, are applied to rank and prioritize the chosen locations. The results highlight the most favorable areas for renewable energy installations in times of disruption and demonstrate the effectiveness of the MCDM approach. The matrix of decision making for selecting renewable energy that is determined by experts is as follow (Table 2-4 and Figure 3):

**Table 2:** Renewable energy type

| Renewable energy type | Economic | Environmental | Technological | Sociality |
|---|---|---|---|---|

| | Investment cost | Payback period | Effect on Climate change | Effect on Natural environment | Efficiency rate | Knowledge of innovative technology | Job criterion | Regional development |
|---|---|---|---|---|---|---|---|---|
| Weight | 0.2 | 0.1 | 0.15 | 0.15 | 0.1 | 0.1 | 0.1 | 0.1 |
| Type | Cost | - | Cost | Cost | - | - | - | - |
| Yazd | 1200000 | 0.55 | 0 | 0 | 0.7 | 0.9 | 10 | 0.85 |
| Tabriz | 1400000 | 0.5 | 0 | 1 | 0.8 | 0.95 | 20 | 0.9 |
| Tehran | 1400000 | 0.56 | 0 | 1 | 0.9 | 0.9 | 20 | 0.95 |
| Kerman | 1200000 | 0.57 | 1 | 1 | 0.8 | 0.96 | 10 | 0.9 |
| Bushehr | 1300000 | 0.6 | 0 | 0 | 0.7 | 0.97 | 20 | 0.95 |

In the numerical results section, the study presents the outcomes derived by utilizing the MCDM method for the selection of renewable energy sources. The findings are based on the evaluation and weighting of criteria, taking into account specific preferences and constraints related to the context. The MCDM results will be demonstrated through rankings, scores, or decision matrices, highlighting the relative performance of various renewable energy alternatives. The analysis will focus on both the merits and constraints of the selected MCDM technique(s), and how they were applied in the process of selecting renewable energy sources.

**Table 3:** Python code for renewable energy assessment by MCDM

```
import numpy as np
from pymcdm.methods import TOPSIS, VIKOR, COPRAS , PROMETHEE_II, COMET, SPOTIS, ARAS,
    COCOSO, CODAS, EDAS, MABAC, MAIRCA, MARCOS, OCRA, MOORA

from pymcdm.helpers import rrankdata

# Define decision matrix (2 criteria, 4 alternative)
alts = np.array([
    [1200000,0.55,0,0,0.7,0.9,10,0.85],
    [1400000,0.5,0,1,0.8,0.95,20,0.9],
    [1400000,0.56,0,1,0.9,0.9,20,0.95],
    [1200000,0.57,1,1,0.8,0.96,10,0.9],
    [1300000,0.6,0,0,0.7,0.97,20,0.95]

], dtype='float')
# print (alts)
```

```
# Define weights and types
weights = np.array([0.2,0.1,0.15,0.15,0.1,0.1,0.1,0.1])
types = np.array([-1,1,-1,-1,1,1,1,1])

# Create object of the method
topsis = TOPSIS()
# Determine preferences and ranking for alternatives
kkk1= topsis(alts, weights, types)
print ("topsis",kkk1)

# Create object of the method
vikor = VIKOR()
# Determine preferences and ranking for alternatives

kkk=vikor(alts, weights, types)

print ("vikor",kkk)

# Create object of the method
copras = COPRAS()
# Determine preferences and ranking for alternatives
kkk=copras(alts, weights, types)
print ("copras",kkk)

# Create object of the method
moora = MOORA()
# Determine preferences and ranking for alternatives
kkk=moora(alts, weights, types)
print ("moora",kkk)

# Create object of the method
mabac = MABAC()
# Determine preferences and ranking for alternatives
kkk=mabac(alts, weights, types)
print ("mabac",kkk)
```

**Table 4:** Results of renewable energy assessment by MCDM

| Renewable energy type | TOPSIS | VIKOR | COPRAS | MOORA | MABAC | Total |
|---|---|---|---|---|---|---|
| Yazd | 0.59 | 0.33 | 0.98 | 0.11 | 0.07 | 0.42 |
| Tabriz | 0.42 | 1.00 | 0.65 | 0.05 | -0.06 | 0.41 |
| Tehran | 0.47 | 0.88 | 0.66 | 0.06 | 0.03 | 0.42 |
| Kerman | 0.49 | 0.70 | 0.45 | -0.11 | -0.03 | 0.30 |
| Bushehr | 0.69 | 0.00 | 1.00 | 0.15 | 0.32 | 0.43 |

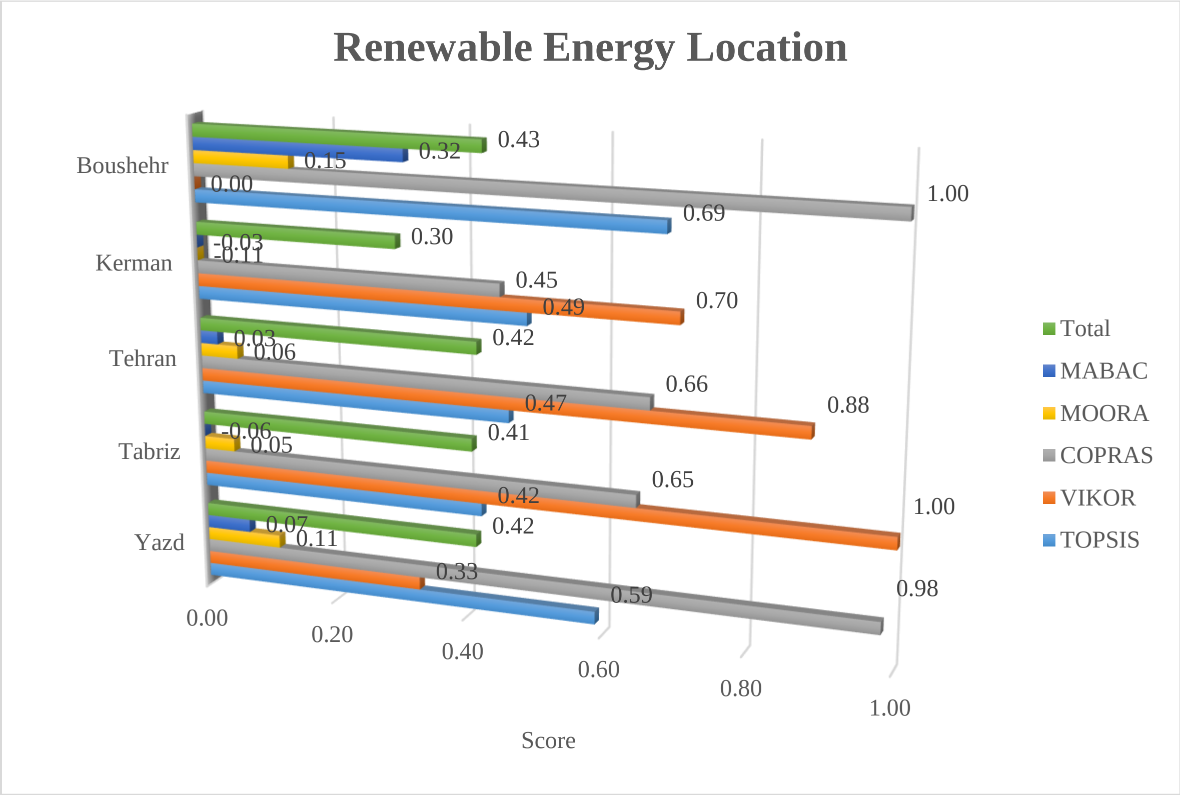


**Figure 3:** Results of factors affecting environmental pollution.

It looks like you have shared the evaluation results for different types of renewable energy using the Multi-Criteria Decision Making (MCDM) method. Each renewable energy type has been given a score. Here are the scores you provided:

- Yazd: 0.42
- Tabriz: 0.41
- Tehran: 0.42
- Kerman: 0.30
- Bushehr: 0.43

These scores indicate the performance or suitability of each renewable energy type according to the criteria considered in the assessment. Higher scores indicate better performance.

## 5. Conclusion

The conclusion section summarizes the key findings from the research. It emphasizes the importance of utilizing MCDM techniques to address location decisions for renewable energy projects in disruption situations. The limitations of the study are acknowledged, and future research directions are suggested. Overall, the conclusions drawn contribute to a better understanding of renewable energy location decision-making under disruptive circumstances.

The evaluation and selection of suitable locations for renewable energy projects are crucial for maximizing their efficiency and minimizing their impact on the environment. In this study, we employed the Multi-Criteria Decision Making (MCDM) method to assess the performance and suitability of different renewable energy types in a disruption situation. By considering various criteria, we have obtained valuable insights into the optimal locations for renewable energy projects.

Based on the assessment results using the MCDM method, the following key findings have emerged:

1. Performance Scores: The scores provided for each renewable energy type, namely Yazd (0.42), Tabriz (0.41), Tehran (0.42), Kerman (0.30), and Bushehr (0.43), reflect their performance or suitability in the disruption situation. Higher scores indicate better performance according to the criteria used in the assessment.

2. Location-specific Suitability: The obtained scores offer a comparative analysis of the renewable energy types in different locations. When considering the disruption situation, it is clear that Bushehr achieved the highest score, indicating its potential as a favorable location for renewable energy projects. On the other hand, Kerman scored the lowest, suggesting that it may not be as suitable for such projects in the given situation.

3. Decision-Making Insights: The MCDM method utilized in this study provides decision-makers with a systematic approach to evaluate and prioritize renewable energy locations. By considering multiple criteria, including environmental compatibility, resource availability, infrastructure support, and energy demand, this method offers a comprehensive framework for making informed decisions.

Implications and Recommendations: The outcomes of this study have several implications for renewable energy development in the context of disruptive situations. The robustness and flexibility of the MCDM method allow for its application in various regions and under diverse disruptions. Hence, policymakers and stakeholders can utilize these findings to identify suitable locations for renewable energy projects during times of disruption. Additionally, future studies could expand the scope of evaluation by incorporating additional criteria and considering technological advancements in the renewable energy sector.

In conclusion, the evaluation of renewable energy locations during disruption situations using the MCDM method has provided valuable insights into their performance and suitability. The obtained scores offer a comparative analysis, highlighting Bushehr as a potentially favorable location and Kerman as a less suitable option. By adopting the MCDM approach, decision-makers can make informed choices when selecting locations for renewable energy projects, considering various criteria and optimizing their contributions to sustainable development goals.

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