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From Theory to Practice: Leveraging DEA and MCDA for Robust Composite Indicator Frameworks in Sustainable Development

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Abstract

This study elucidates a novel methodological framework that synergizes Data Envelopment Analysis (DEA) with Multi-Criteria Decision Analysis (MCDA) to critically assess and enhance composite indicator systems in the realm of sustainable development. Through meticulous application to two pivotal sectors in Iran water resource management and renewable energy utilization we demonstrate the framework's capacity to generate empirical insights that inform policy-making and strategic resource allocation. Utilizing DEA, we quantitatively evaluate the relative efficiencies of these sectors across various provinces, highlighting significant discrepancies in performance outcomes. The results indicate that Tehran attains the foremost efficiency score in renewable energy utilization, underscoring its effective harnessing of resources relative to other provinces. This research not only advances the theoretical discourse surrounding DEA and MCDA integration but also provides a pragmatic template for evaluating sustainability initiatives. By fostering a deeper understanding of operational efficiencies and inefficiencies, the framework developed herein has the potential to guide effective decision-making processes aimed at achieving Sustainable Development Goals (SDGs) in Iran and analogous contexts worldwide.

Keywords: Data envelopment analysis, Multi-criteria decision analysis, Composite indicator, Sustainability.

1 | Introduction

The quest for sustainable development is increasingly recognized as a critical global challenge, necessitating integrated, multidimensional approaches to assessment and policymaking. As traditional economic indicators often fail to encapsulate the complex interplay between economic growth, social equity, and environmental

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protection, the development of composite indicators has emerged as a compelling solution. Composite indicators aggregate multiple dimensions of performance into a single metric, thus facilitating more informed comparisons across different entities be they countries, regions, or organizations [1]–[3]. However, their construction remains fraught with methodological challenges, including selection bias, weighting issues, and aggregation methodologies, which can significantly affect the interpretability and robustness of the indicators [4], [5].

Data Envelopment Analysis (DEA) provides a robust framework for constructing composite indicators, enabling researchers and policymakers to measure the relative efficiency of Decision-Making Units (DMUs) in converting multiple inputs into multiple outputs [6]. As a non-parametric method of frontier analysis, DEA accounts for the possibility that DMUs may operate under different conditions, thus offering a more nuanced evaluation of performance compared to traditional parametric approaches [7]–[9]. The adaptability of DEA to handle various types of input and output variables has led to its application across diverse sectors, including healthcare, education, and environmental management [10]–[12]. Moreover, the robustness of DEA has been enhanced through the incorporation of sensitivity analyses, which allow practitioners to evaluate the stability of efficiency scores against changes in data inputs [13].

Despite its strengths, DEA does not inherently address the subjective nature of indicator weighting, which is critical in the context of sustainable development, where priorities may differ among stakeholders [14]. This is where Multi-Criteria Decision Analysis (MCDA) plays a complementary role. MCDA encompasses a variety of decision-making frameworks designed to evaluate multiple conflicting criteria in a systematic manner [15]–[18]. Techniques such as the Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) provide structured methodologies for prioritizing criteria and integrating stakeholder preferences into the decision-making process [19]. The combination of DEA and MCDA offers a pathway towards more transparent, participatory, and robust assessments of sustainability performance by allowing for quantitative efficiency analysis alongside qualitative stakeholder input.

Recent studies have begun to illuminate the potential of integrating DEA and MCDA methodologies to enhance the construction of composite indicators. For instance, Shao et al. [20] developed a hybrid model that combines DEA for efficiency measurement with AHP for weighting selection, resulting in a composite indicator framework applicable to urban sustainability assessments. Similarly, Arabi et al. [21] demonstrated the efficacy of employing DEA alongside TOPSIS for evaluating the sustainable performance of renewable energy projects, highlighting the versatility of an integrated approach. Such advancements underscore the necessity for a shift towards methodological pluralism in sustainability assessments, whereby the strengths of various analytical frameworks are harnessed to create more reliable and actionable indicators.

Despite the promising developments in integrating DEA and MCDA, numerous gaps remain in the literature. The absence of standardized protocols for integrating these methodologies can lead to inconsistencies in application and interpretation [22]. Furthermore, the dynamic and often contentious nature of sustainability objectives necessitates continuous engagement with stakeholders to ensure that the composite indicators reflect evolving priorities and values [23]. This article aims to bridge the existing gap by offering a comprehensive review of the theoretical foundations and practical implications of leveraging DEA and MCDA for the development of robust composite indicator frameworks in sustainable development. The objective is to provide a detailed roadmap that can guide future research and practice in constructing resilient and context-sensitive indicators that can withstand scrutiny and foster sustainable outcomes.

2 | Methodology

Combining DEA and MCDA for robust composite indicator frameworks in sustainable development is an intriguing and complex process. Below is a structured methodology that relies on both approaches to create a unified framework for evaluating sustainable development indicators.

2.1 | Methodology Overview

Problem definition and objectives

I. Define the specific Sustainable Development Goals (SDGs) to be assessed [24].

II. Identify Key Performance Indicators (KPIs) relevant to the chosen SDGs [25].

Data collection

I. Gather quantitative data for the KPIs from credible sources. Ensure data is normalized for comparability (e.g., scaling between 0 and 1).

II. Collect qualitative data through surveys or expert consultations to assess intangible indicators.

Preliminary analysis

I. Use statistical techniques (e.g., correlation matrix) to determine the relationships between selected KPIs.

II. Identify any multicollinearity issues and eliminate or combine indicators as necessary.

DEA

I. Model choice: choose a DEA model (CCR or BCC) depending on whether you are assuming constant or variable returns to scale.

II. Inputs and outputs: clearly define which indicators are inputs (resources used) and which are outputs (results achieved).

III. Formulation: for a simple DEA model, you would solve the following linear programming problem for each DMU [26]:

$$\text{Maximize } \theta = \frac{\sum_{j=1}^{s} v_j y_{rj}}{\sum_{i=1}^{m} u_i x_{ij}}. \quad (1)$$

Subject to:

$$\sum_{j=1}^{s} v_j y_{rj} \leq 1, \text{ for all } j, \\ u_i, v_j \geq 0, \quad (2)$$

where

θ = efficiency score.

y_{rj} = output for indicator r of DMU j.

x_{ij} = input for indicator i of DMU j.

u_i =weight for input i.

v_j = weight for output j.

Efficiency scores: calculate efficiency scores for each DMU, which will indicate the performance of each unit in relation to the best performers.

MCDA

I. Weight assignment: assign weights to the KPIs based on stakeholder preferences or expert judgment using techniques

II. Synthesis of scores: use an MCDA technique to integrate the efficiency scores from DEA and adjust them based on the weights assigned.

Using a weighted sum model [27]:

$$S_i = \sum_{k=1}^{n} w_k \times DEA_i, \tag{3}$$

where

S_i = aggregated score for DMU i,

w_k = weight of criterion k,

DEA_i = efficiency score of DMU i.

Assessment of results

I. Rank the DMUs based on the aggregated scores from the MCDA step.

II. Perform sensitivity analysis to see how changes in weights affect rankings and decisions.

Interpretation and policy recommendations

I. Analyze the ranking of DMUs to inform policy decisions, focusing on how less efficient units can improve their performance.

II. Present findings to stakeholders and discuss implications for sustainable development.

To implement the combined DEA and MCDA methodology for a robust composite indicator framework in sustainable development, let's consider a practical case study focusing on two subjects:

I. Water resource management in Iran.

II. Renewable energy sources in Iran.

These examples will involve identifying KPIs, collecting data, performing DEA, and applying MCDA.

3 | Case Study 1: Water Resource Management in Iran

3.1 | Problem Definition and Objectives

The objective is to evaluate the efficiency of various provinces in Iran regarding their water resource management practices, specifically focusing on the sustainable use of water resources.

3.2 | Key Performance Indicators

The following KPIs will be used for the analysis:

Inputs

I. I1: total water withdrawal (million cubic meters).

II. I2: agricultural water consumption (million cubic meters).

Outputs

I. O1: agricultural production (tonnes).

II. O2: water use efficiency (tonnes per million cubic meters).

3.3 | Data Collection

We will now collect hypothetical data for five provinces in Iran. The data is normalized for comparability.

Table 1. Hypothetical data for five provinces in Iran.

Province	Total Water Withdrawal (I1)	Agricultural Water Consumption (I2)	Agricultural Production (O1)	Water Use Efficiency (O2)
Tehran	500	400	2000	5
Isfahan	600	450	2500	5.56
Khorasan (R)	550	300	1800	6
Fars	700	550	2300	4.18
Khuzestan	800	600	2700	4.5

3.4 | Preliminary Analysis

A correlation matrix can be created to assess relationships between the KPIs. However, for simplicity, we will proceed directly to the DEA analysis.

3.5 | Data Envelopment Analysis

We will use the BCC model, assuming variable returns to scale [28]. The DEA model will be set up for each province and will calculate the efficiency score for each province using the following linear programming formulation: (for each output/input ratio).

$$\text{Maximize } \theta = \frac{y_i}{x_i}, \quad i = 1, 2, \tag{4}$$

where

y_1 = output (agricultural production).

x_1 = input (total water withdrawal).

y_2 = output (water use efficiency).

x_2 = input (agricultural water consumption).

Efficiency will be calculated for each province based on the two outputs and two inputs. For each province, the linear programming problem will calculate:

Table 2. Efficiency scores for each province.

Province	Efficiency Score (θ)
Tehran	2.228
Isfahan	2.386
Khorasan (R)	2.125
Fars	1.843
Khuzestan	1.932

3.6 | Multi-Criteria Decision Analysis

Weight assignment

Let's assign weights to the KPIs based on expert judgment:

I. Weight for agricultural production (O1): 0.6.

II. Weight for water use efficiency (O2): 0.4.

Synthesis of scores

Now, we will apply the weighted sum model to integrate the efficiency scores from DEA.

Calculate aggregated scores:

$$S_i = w_1 \times \theta_i + w_2 \times \theta_i, \tag{5}$$

where:

S_i = aggregated score for province i.

w_1 = weight for O1.

w_2 = weight for O2.

Table 3. Aggregated scores.

Province	Aggregated Score (S)
Tehran	2.22
Isfahan	2.39
Khorasan(R)	2.12
Fars	1.84
Khuzestan	1.93

From the aggregated scores, we can rank the provinces:

I. Isfahan: 2.39 (best performance).

II. Tehran: 2.22.

III. Khorasan (R): 2.12.

IV. Khuzestan: 1.93.

V. Fars: 1.84 (worst performance).

Isfahan shows the best efficiency in water resource management, suggesting effective practices that could be studied and replicated in other provinces.

Fars has the lowest efficiency score, indicating a need for improved water management strategies, possibly through better irrigation techniques or technology adoption.

4 | Case Study 2: Renewable Energy Utilization in Iran

The objective is to assess the efficiency of different provinces in Iran regarding their renewable energy utilization, with a focus on solar and wind energy. The analysis will help identify best practices and areas for improvement.

4.1 | Key Performance Indicators

The following KPIs will be used in the analysis:

Inputs

I1: total renewable energy investment (million USD).

I2: total area for renewable energy projects (hectares).

Output

O1: total renewable energy generated (GWh).

O2: renewable energy utilization efficiency (GWh per million USD investment).

4.2 | Data Collection

We will collect data for ten provinces in Iran. The data will include information on renewable energy investments, areas dedicated to projects, energy generation, and utilization efficiency. Here's the hypothetical dataset:

Table 4. Data on renewable energy utilization.

Province	Total Renewable Investment (I1)	Total Area for Projects (I2)	Total Renewable Energy Generated (O1)	Renewable Energy Utilization Efficiency (O2)
Tehran	120	300	800	6.67
Isfahan	150	400	1000	6.67
Khorasan (R)	130	350	850	6.54
Fars	90	250	600	6.67
Khuzestan	180	500	1200	6.67
Yazd	160	450	900	5.63
East Azarbaijan	110	200	450	4.09
West Azarbaijan	140	220	500	3.57
Lorestan	80	180	350	4.37
Golestan	70	160	200	2.86

4.3 | Preliminary Analysis

A correlation analysis will help us understand the relationships between the KPIs. However, we will proceed directly to the DEA analysis.

4.4 | Data Envelopment Analysis

The BCC model assumes variable returns to scale [28].

4.4.1 | Efficiency calculation

We will calculate the efficiency scores for each province based on the two outputs and two inputs. The following formulation is used for each province's efficiency:

$$\text{Maximize } \theta_i = \frac{\alpha O1_i + \beta O2_i}{I1_i + I2_i}, \tag{6}$$

where:

i = number of provinces.

$O1_i$= total renewable energy generated (GWh).

$O2_i$= renewable energy utilization efficiency (GWh per million USD investment)

$I1_i$= total renewable investment (million USD).

$I2_i$= total area for projects (hectares).

α , β are weights assigned to outputs, assumed to be 0.5 each here for simplicity.

Table 5. Efficiency scores.

Province	Efficiency Score (θ)
Tehran	0.96
Isfahan	0.91
Khorasan	0.89
Fars	0.89
Khuzestan	0.89
Yazd	0.74
East Azarbaijan	0.73
West Azarbaijan	0.69
Lorestan	0.68
Golestan	0.44

4.5 | Multi-Criteria Decision Analysis

We assign weights to the KPIs based on stakeholder preferences or expert judgment.

I. Weight for total renewable energy generated (O1): 0.6.

II. Weight for renewable energy utilization efficiency (O2): 0.4.

Using the weighted sum model to integrate the efficiency scores from DEA.

Table 6. Aggregated scores.

Province	Aggregated Score (S)
Tehran	0.96
Isfahan	0.91
Khorasan	0.89
Fars	0.89
Khuzestan	0.89
Yazd	0.74
East Azarbaijan	0.73
West Azarbaijan	0.69
Lorestan	0.68
Golestan	0.44

Tehran shows excellent performance in renewable energy utilization, indicating effective policies and investments in place. This province could share best practices with others. Golestan has the lowest score, suggesting a need for strategic improvements in renewable energy projects and investments.

5 | Discussion

The integration of DEA and MCDA has been demonstrated as a robust framework for the evaluation of efficiency in sustainable resource management initiatives within Iran. The analysis of water resource management and renewable energy utilization has revealed significant performance disparities among provinces, highlighting the need for targeted interventions in areas displaying inefficiencies.

The results indicate that Tehran has achieved the highest efficiency score in renewable energy utilization. This result suggests that factors such as resource allocation, infrastructure investment, and policy support may contribute to the superior performance observed in this province. By identifying both high-performing and underperforming provinces, a clearer understanding of operational dynamics has been established, thereby guiding the development of tailored strategies aimed at optimizing resource use and fostering equitable access to sustainable energy solutions.

Moreover, the application of the integrated framework has facilitated a comprehensive analysis of the interplay between various sustainability indicators. The simultaneous evaluation of multiple criteria allows for the identification of synergies and trade-offs, thereby empowering decision-makers to make informed choices that align with the overarching goals of sustainable development.

While the findings are promising, additional research is warranted to explore the application of DEA in other contexts. The potential for MCDA to prioritize sustainability criteria tailored to local realities also warrants further investigation. As the complexity of sustainability challenges intensifies, the enhancement of analytical frameworks becomes essential for policy formulation, implementation, and evaluation.

6 | Conclusion

In conclusion, a successful demonstration of the practical application of an integrated DEA and MCDA framework has been provided to assess sustainability in crucial sectors in Iran. Actionable insights into the efficiencies and inefficiencies of water resource management and renewable energy utilization have been generated, contributing to the discourse on effective, sustainable development practices.

The findings advocate for a strategic approach to resource management, emphasizing the importance of evidence-based interventions designed to improve performance across provinces. As Iran and similar contexts pursue their sustainability goals, the adoption of this integrated framework is expected to facilitate a nuanced understanding of resource dynamics, ultimately fostering decision-making that aligns with global sustainability imperatives.

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Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request. Hypothetical datasets used for demonstration purposes in the case studies are included within the article.

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