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Metaheuristic-Driven Optimization for Complex Multidimensional Decision-Making: A Case Study on Prioritizing Airport Locations

Nazila Razi*
Rouhollah Bagheri†
Hamed Pourabbas‡

Abstract

Effective management accounting procedures necessitate a thorough evaluation of discrepancies and variability in decision-making processes. However, conventional statistical measures often generate misleading results. In this research, we present the mean squares of criteria and alternatives (MESCA) to multifaceted decision-making, suitable for scenarios involving conflicting or competing constraints, this in turn, bolsters the confidence levels of decision-makers, ultimately fostering more informed and enhanced decision-making processes. In this case study, we employ a metaheuristic approach to determine the optimal airport location, contrasting it with the established simultaneous evaluation of criteria and alternatives (SECA) model. Our research follows a deductive, survey-based methodology, using ten indicators to prioritize cities for airport placement. The comparative analysis between the MESCA and the SECA accentuates the advantages of metaheuristic approach over the SECA model, offering valuable insights for effective management decisions. Our findings confirm that both approaches concur in identifying the same city as the most favorable alternative based on the established criteria. But there is evidence that MESCA method surpasses the SECA model in terms of simplicity, flexibility, and cost-effectiveness, crucial considerations in the realm of management accounting. These revelations provide essential guidance to airport specialists and decision-makers when navigating constraints and selecting optimal airport locations.

Keywords: optimization, multidimensional decision-making, metaheuristic technique, resource allocation, MESCA, SECA.

I. INTRODUCTION

In the realm of management accounting, it is imperative to acknowledge the importance of effectively evaluating errors and variability in decision-making processes. Traditional statistical measures such as the sum of squares of deviations, along with metrics like coefficient of variation and root mean square error, are often employed in management accounting practices. However, these metrices can be misleading indicators of average errors or variability, potentially leading to suboptimal decisions. Management accounting methodologies that solely rely on the sum of squares have been observed to

* Associate Dean of teaching & learning and research. Crown Institute of Higher Education, Sydney, Australia. Phone: +61299550488, Email: nazila.razi@cihe.edu.au. Web page: https://cihe.edu.au.

† Corresponding author. Assistant professor. Department of Management, Faculty of Administrative and Economic Sciences, Ferdowsi University, Mashhad, Iran. E-mail: rbagheri@um.ac.ir.

‡ PhD. candidate. Department of Management, Islamic Azad University, Tehran, Iran. Email: hpourabbas@au.ac.ir.

unveil at least two distinct patterns within the data. These patterns point to the impact of variations on the measurement of errors on the sum of squares, which can distort the accurate evaluation of their significance from (Willmott et al., 2009). Multiple criteria decision making (MCDM) techniques encompass various methodologies, which can be broadly categorized into two classes as outlined by Zimmermann (1991): Zimmermann divided MCDM into two directions: 1) Multi-attribute decision making (MADM), which focuses on discrete preference domains, and 2) Multi-objective decision making (MODM), involving the simultaneous optimization of several competing objectives (Zimmermann, 1991).

Multi-objective decision-making offers an effective approach for optimizing complex, constrained problems where conflicting goals need simultaneous consideration. The evaluation of each goal may vary significantly, for instance, one goal might prioritize profit maximization, while another focuses on minimizing workforce costs. Notably, this approach accommodates diverse objectives without inherent contradictions. Multi-objective decision-making is particularly well-suited for tasks involving design and planning, as it excels in optimizing the allocation of limited resources. Given the prevalent occurrence of competing or even contradictory constraints in real-world scenarios, decision makers often turn to MODM methods to simultaneously address multiple objectives. In this context, mathematical programming techniques are frequently employed to address these optimization challenges (Jahan & Edwards, 2013).

MCDM is intricately associated with the concept of Rational Choice, which posits that human actions are driven by financial incentives and the potential for economic benefit. This fundamental premise has paved the way for the development of structured, often predictive models of human behavior. It posits that individuals generally tend to make rational decisions within specific constraints, drawing upon available information within their unique contexts. Human behaviour encompasses a continuum of both rational and non-rational elements (Duxbury et al., 2005). Theories of rational choice advocate that individuals should foresee the consequences of various choices and opt for alternatives that offer them the greatest advantage. When individuals encounter situations where they cannot attain their ideal outcomes, they must actively seek solutions to address their challenges. This theory suggests that humans operate like high-performance computers capable of rapidly resolving intricate problems (Elster, 2001).

Meta-heuristic algorithms are designed to address the challenges of avoiding local optima, as highlighted by Glover and Sörensen (2015). These algorithms offer a general strategy for solving a wide range of problems, as demonstrated by Juan et al. (2015) and Doering et al. (2019). The crucial element lies in defining the problem in alignment with the chosen strategy, as emphasized by Chiandussi et al. (2012). Given the often-constrained nature of time, and resources, it becomes imperative to optimize their utilization (Jalaee et al., 2021). Real-world scenarios frequently present nonlinear and multidimensional optimization challenges, leading to competing objectives. As a result, finding optimal or near-optimal solutions (Sitorus & Brito-Parada, 2020; Yannis et al., 2020), even for common goals, can be inherently challenging, echoing the complexities (Sharon et al., 2015). Galagederaa et al. (2020) endeavor to address these challenges by presenting the MESCA metaheuristic method in the context of airport location decision-making. The study emphasizes that the selection of airport sites experts a profound impact on the mobility of people and goods in particular areas, highlighting the pivotal consequences of ill-advised airport placement in both the realms of human welfare and financial consequences.

In another study titled "Approximate Computation of Storage Functions for Discrete-Time Systems Using Sum-of-Squares Techniques," the authors propose a methodology for the automated computation of dissipation in discrete-time systems. This approach, which leverages numerical techniques and sum-of-squares strategies, proves invaluable in addressing system constraints and in developing Taylor approximations for nonlinear cost functions, ultimately enabling the approximate assessment of near-storage capabilities (Pirkelmann et al., 2019). Additionally, the article "Mean Squared (MBDoE): Version," explores the utilization of MBDoE to enhance mathematical methods for real-world applications. In traditional optimization techniques for MBDoE, challenges may arise due to inappropriate matrix formatting, presenting practical difficulties. This work introduces an alternative optimal index designed to mitigate these issues, with its components contingent on various parameters (Kim et al., 2022).

The article "Global Estimates in Sobolev Spaces for Homogeneous Hörmander Sums of Squares," delves into the realm of Hörmander sums of squares, comprising sets of vector fields within the Euclidean space R^n. The authors present precise estimations for the local function associated with general Hörmander squares, skillfully incorporating the homogeneity property of Xj and a universal lifting technique for homogeneous vector fields (Biagi et al., 2021).

The primary objective of this research extends into the realm of management accounting, intending to offer invaluable support to airport specialists and designers. The aim is to guide them in navigating the complexities arising from various constraints, and to introduce innovative approaches that can effectively mitigate the detrimental consequences of suboptimal airport locations. The importance of efficient resources allocation, cost control and strategic financial decisions is underscore. Furthermore, this article contributes to enhancing the utility of MESCA method that could be valuable in the domain of management accounting, empowering decision-makers to make informed choices form the extensive array of decision-making methods available. It recognizes the significance of precision in financial decisions and underscores the relevance of strategic resource allocation and optimization in financial planning. Additionally, this work delves into the identification of limitations in the SECA model, a crucial aspect within the purview of management accounting. By addressing these limitations, the article aims to augment the efficiency of decision-making processes and ultimately contribute to more effective financial management and resource allocation strategies.

II. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. Methodology

This study introduces the application of the MESCA heuristic technique as a fundamental tool to enhance decision-making in the prioritization of several cities in airport allocation. In terms of research orientation, this study aligns with applied research, predominantly employing quantitative methodologies. The research methodology follows a deductive, survey-based, and descriptive approach in consonance with its objectives. The research population encompasses individuals holding managerial, supervisory, and expert positions within the airport and air navigation company. Their selection is based on specific criteria such as experience level, education, educational background, and work history. In 2021, this population consisted of 451 individuals, from which a systematic sample of 62 individuals were chosen. Data collection was carried out over a defined period through a questionnaire designed by the researcher. Initially, ten pivotal indicators were identified from and extensive literature review, chosen from a total of 45 indicators believed to influence the selection of the Delphi airport. These ten selected indicators include: average annual household income (in thousands of Rials) population, future expansion, distance from the nearest airport, air site visitors, utilized airports (commercial, military, etc.), safety and adherence to standards, topography, economic value and attraction to passengers (number of domestic travelers per year, in hundreds) Statistical Centre of Iran (2017).

In the second stage, the MESCA metaheuristic technique was employed, and its outcomes were compared with those of the SECA model. It is essential to understand the critical role of these ten indicators in shaping the research framework and analysis.

2.1.1. Geographical Description

East Azerbaijan, one of Iran's provinces, is nested in the northwestern part of the country. Encompassing an expansive landmass of 45,491 square kilometers, it constitutes roughly 2.8% of the total land area of the country. Geographically, East Azerbaijan province finds its place at the northwestern juncture of the Iranian plateau, where the Alborz and Zagros Mountain ranges converge. Its northern border spans 235 kilometers and is shared with Azerbaijan, Armenia, and the Nakhichevan Autonomous Republic of Azerbaijan demarcated by the flowing waters of the Aras River. To the west and southwest, it abuts West Azerbaijan, while Zanjan province lies to the south, and Ardabil province to the east. Within East Azerbaijan's expanse, you'll find 12 cities, 31 towns, 30 districts, and a network of 3,282 villages. The climate that graces this province is broadly characterized as cold and arid, but its diverse topography gives rise to a climate that is uniquely its own. Predominantly recognized for its cold, mountainous terrain, East Azarbaijan is classified as a semi-arid region. It experiences an average annual precipitation of 250 to 300 millimeters. East Azerbaijan Province is divided into four zones a) Northeast cities (Ahar, Khodaafarin, Klibar), b) Northwest cities (Jolfa), c) Southwest cities (Malekan, Bonab) and d) Southeast cities (Mianeh, Charavimagh, Hashtrod). Other cities have been omitted considering their proximity to the airport.

2.1.2. Key Criteria for Airport Location Selection

The process of determining a suitable location for an airport is intricately tied to the airport classification, as discussed by Chung et al. (2016). Those entrusted with this decision-making for new airport projects should initiate the process by identifying the primary indicators, as highlighted by Gibbons and Wu (2020). Drawing from research conducted by the International Civil Aviation Organization (ICAO) on airport placement, the criteria influencing the optimal airport location can be organized into four distinct categories, as stipulated by ICAO in 1997.

Insert Table 1 here.

III. RESEARCH METHODOLOGY

3.1. Evaluation of MESCA Method

The MESCA technique is classified as a mitigation method in the realm of multi-attribute decision-making within specific sub-functional groups. In this approach, the need for complex calculations is minimized. Decision-makers can harness the power of the MESCA method through the introduction of a confidence level. This method involves a sequence of steps, considering an alternative denoted as 'M' and an indicator labeled 'N'. multiple alternatives are represented as 'xij,' while various indicators are denoted as 'xj.' 'Xij' signifies the rank value for alternative 'I' and index 'j.' By determining the weights of these indicators, one can readily apply this technique. The following steps outline the procedure for employing this method.

Table 1
Key Criteria for Airport Location Determination

Criteria	Indicators
Physical Factors	• Access to the transportation system • Land availability for future expansion • Dual-purpose usage of the airport (military and business)
Aviation and Geographical Factors	• Climatic conditions • Surrounding airports' positions • Barriers' locations – Topography
Economic Factors	• Cost and benefit analysis • Administration and maintenance costs • Fuel consumption
Environmental Factors	• Environmental impact assessments • Noise pollution • Compliance with regional planning

Step 1. Formulation of a Decision Matrix

Based on the number of alternatives, criteria, and the comprehensive evaluation of all available options, the decision matrix is formed as follows:

Table 2
Decision Tree

$$x = \begin{bmatrix} x11 & \cdots & x1n \\ \vdots & \ddots & \vdots \\ xm1 & \cdots & xmn \end{bmatrix}$$

Step 2. Scaling Indicators and Quantifying Qualitative Indices through Pairwise Comparison

In this context, alternative (Ai) are characterized by two types of indicators (xj): quantitative (e.g cost, capacity) and qualitative attributes (e.g convenience, aesthetic), assessed using a 5-point Likert scale.

Step 3. Normalization of the Decision Matrix

In the first set of relationships, (Relation 1), PC comprises criteria with a profit or positive aspect, while in the second set (Relation 2), DC includes criteria associated with costs or negative impacts.

$$X_{ij}^{N} = \begin{cases} \dfrac{X_{ij}}{\max_k X_{kj}} & \text{if } j \in PC, \\ \dfrac{\min_k X_{kj}}{X_{ij}} & \text{if } j \in DC, \end{cases} \qquad \text{1-2}$$

Step 4. Employing Metaheuristic Technique for Weighting Indicator Evaluation

Utilizing metaheuristic approach to determine indicator weights, this method necessitates the use of a criterion-alternative matrix.

$$SSA = \sum_{i=1}^{m} \frac{vj.^2}{n} - \frac{v..^2}{mn} \qquad 3$$

$$MSA = \frac{SSA}{2mn^4} \qquad 4$$

$$Cj = \frac{\bar{V}J.^{MSA}}{N} \qquad 5$$

$$\frac{(vi.)^{msa} * vi.}{n} = \overline{vi.} \qquad 6$$

$$\frac{vi.}{\sum_{j=1}^{n}(v..-vij)^{msa}} = \overline{vi.} \qquad 7$$

$$\sum_{j=1}^{n}(v..-vij)^{msa} = n \qquad 8$$

$$\frac{\mathbf{vi.}}{\sum_{j=1}^{n}(v..-vij)^{msa}} = \overline{\mathbf{vi.}} \quad \text{...} \quad 9$$

$$\sum_{i=1}^{m}(\mathbf{v..}-\mathbf{vij})^{msa} = \mathbf{m} \quad \text{..} \quad 10$$

$$\frac{(\mathbf{vj.})^{msa} * \mathbf{vj.}}{\mathbf{m}} = \overline{\mathbf{vj.}} \quad \text{...} \quad 11$$

Table 3
Parameters of the Technique

Parameter	
Alternative	m
Attribute	n
Sum of each alternative	vi.
Sum of each attribute	Vj.
Normalization of each data in weighted decision matrix	vij
Sum of all the entries in the weighted decision matrix	v..
Importance of every alternative	ci
Mean of each criterion	$\bar{v}$i.
Mean of each alternative	$\bar{v}$j.
Sum of squares of alternatives and attributes	SSA
Mean squares for alternatives and attributes	MSA

Step 5. Calculating the Normalized Weighted Decision Matrix

In this step, the obtained criteria weights from the entropy methods are multiplied with the normal matrix to derive the weighted matrix.

$$\mathbf{V = X_{ij}^{N} * Cij} \quad \text{...} \quad 12$$

Step 6. Assessing the Significance of Each Alternative

By employing the mean squares of the alternatives and calculating the mean of each level within the normalized weighted decision matrix, we determine the importance of each alternative. With the constraint that the sum of Ci equals one, the criterion with the highest value becomes our selection.

$$\mathbf{Ci} = \frac{\overline{\mathbf{VI.}}^{\mathbf{MSA}}}{\mathbf{M}} \quad \text{...} \quad 13$$

$$\sum_{i=1}^{m} ci = 1 \quad \text{...} \quad 14$$

3.2. Evaluation of SECA Method

SECA an approach to multi criteria decision-making, designed to calculate both the total scores of different alternatives and the wights of criteria simultaneously. SECA achieves this using multi-objective nonlinear mathematical logic model. This method allows decision-makers to assess and rank various alternatives while considering multiple criteria (Keshavarz et al., 2018) in a unified process, providing a comprehensive and efficient way to make complex decisions. The following steps outline the procedure for employing this method.

Step 1. Formation of a Decision Matrix

The decision matrix is a tabular representation with columns representing decision criteria and rows denoting problem alternatives.

Step 2. Normalization of the decision matrix

Within Relation 15, PC encompasses criteria with a profit or positive orientation, while Relation 16 incorporates criteria associated with costs or negative impacts.

$$X_{ij}^{N} = \begin{cases} \dfrac{X_{ij}}{\max_k X_{kj}} & \textbf{if } j \in PC, \\ \dfrac{\min_k X_{kj}}{X_{ij}} & \textbf{if } j \in DC, \end{cases} \quad \text{...} \quad 15\text{-}16$$

Step 3. Formulation of the Optimization Model

To create the optimization model, we begin by assessing the standard deviation and correlation coefficient among the elements. Equation 17, representated as:

$$\pi j=\sum_{l=1}^{m}(1-r_{jl}) \quad 17$$

Equations 18 and 19 introduce normalized values (σj) and (πj), which show the variability within a single criterion (σj) and the degree of difference between the criterion j and the other criteria (πj).

$$\sigma j^{N}=\frac{\sigma_j}{\sum_{l=1}^{m}\sigma_l} \quad 18$$

$$\pi j^{N}=\frac{\pi_j}{\sum_{l=1}^{m}\pi_l} \quad 19$$

Based on these calculations, we derive a nonlinear multi-objective planning model as follows:

$$\text{Max } Z=\lambda_a-\beta(\lambda_b+\lambda_c) \quad 20$$

$$\text{s.t. } \lambda a\leq S_i \quad \forall_i \in \{1,2,\ldots n\} \quad 21$$

$$Si=\sum_{j=1}^{m}WjXij^{N} \quad \forall_i \in \{1,2,\ldots n\} \quad 22$$

$$\lambda b=\sum_{J=1}^{M}(W_j-\sigma_j^{N})^2 \quad 23$$

$$\lambda c=\sum_{j=1}^{m}(W_j-\pi_j^{N})^2 \quad 24$$

$$\sum_{j=1}^{m}W_j=1 \quad 25$$

$$W_j\leq 1, \forall_j \in \{1,2,\ldots,m\} \quad 26$$

$$W_j\geq \varepsilon, \forall_j \in \{1,2,\ldots,m\} \quad 27$$

The multi-objective model can potentially be transformed into a single-objective model. The primary objective, as stated in Relation 20, aims to maximize the minimum overall performance score for the available alternatives.

This is achieved by minimizing deviations from reference points, which are adjusted by the β coefficient, impacting the significance of achieving reference points for weighted criteria. Relation 21 sets a minimum threshold for the overall performance score of each alternative (Si). Relation 22 computes the cumulative weight of each criterion in the standard matrix. Relations 23 and 24 determine the total deviation of the weighted criteria from the reference points, using standard deviation and correlation measurements for each criterion. Relation 25 ensures that the sum of the weights equals 1, and Relations 26 and 27 establish that the weight obtained within the range of zero to one.

IV. RESULTS AND DISCUSSIONS

4.1. Overall Results and Findings

The analysis of the collected data is included in Table 4. The table shows the correlation between various variables. The table displays the correlations coefficients and their corresponding significance levels (Sig. 2-tailed) for pairs of variables (A with B and B with C).

Table 4
Correlation

			A	B
Kendall's tau_b	A	Correlation Coefficient	1.000	0.993*
		Sig. (2-tailed)	-	0.016
		N	2	2
	B	Correlation Coefficient	0.993*	1.000
		Sig. (2-tailed)	0.016	-
		N	2	2

As evident from the Table, the correlation coefficient between A and B is 0.993, indicating a strong positive relationship between these variables. The significance level of (0.016) is less than 0.05, suggesting that this correlation is statistically significant. Similarly, the correlation coefficient between B and C is also 0.993, implying a strong positive relationship between these two variables and there is a significant statistical correlation.

4.1.1. Analyzing Findings Using MESCA Method

In this study, the result is the design of a metaheuristic technique for use in spatial information systems using multi-criteria decision-making methods. The final choice is the appropriate alternative that the results of the evaluation of this issue are stated in this part of the research.

Step 1. Formulation of a Decision Matrix

In this initial step, we construct a decision matrix comprising various alternatives, which are assessed based on multiple indicators. This process enables the identification of the most suitable alternative and establishes a priority order for these alternatives.

Table 5
Decision Matrix

Attribute / Alternative	1	2	3	4	5	6	7	8	9	10
Northeast	**453230**	**233375**	H	H	L	V. H.	V. H.	L	L	89
Northwest	**453230**	**67550**	L	M	L	V. H.	V. H.	L	V. L.	26
Southwest	**453230**	**256509**	L	M	M	V. H.	V. H.	H	M	98
Southeast	**453230**	**263583**	H	H	M	V. H.	V. H.	L	M	101

Notes: L= Low; V. L.= Very Low; M= Medium; H= High; and VH= Very High.

Step 2. Calculating the Sum and Mean Squares of the Alternatives

Following the relationship outlined in steps 4-6 (section 2.3.), we calculate both the sum and mean of the squares of the alternatives. Specifically, step 4-6 informs us about the method's reliance on the mean of the alternatives. Consequently, we compute the sum of the alternative squares, resulting in a value of 0.206, and the mean of the alternative squares, which amounts to 2.57×10^{-6}.

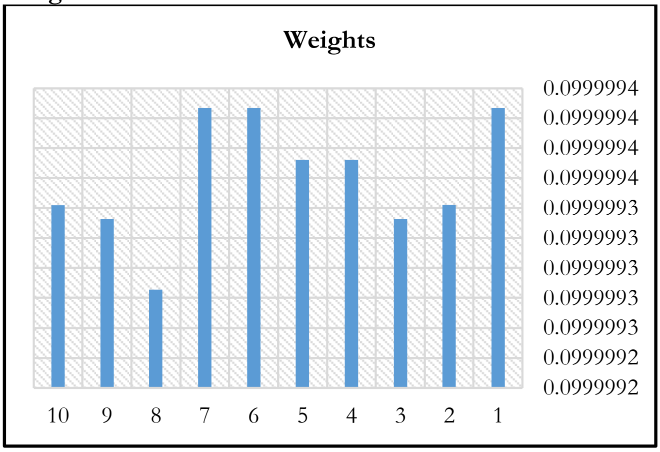
Step 3. Determining Alternative Importance

This step involves using equation 13, based on the normalized weight matrix, to determine the importance of each alternative. It's noteworthy that the total importance of the alternatives sums up to 1, and any alternative with a higher value serves as the selection criterion. The importance values for each alternative are as follows:

C1= 0/249998426
C2= 0/249998224
C3= 0/249998463
C4= 0/249998484

For these importance values, we can infer that the fourth alternative (Southeast) holds the highes priority making it the first choice. The third alternative (Southwest) secures the second priority, followed by the first alternative (Northeast) in the third position, ang the second alternative (Nortwest) as the least preferred, occupying the fourth position. In summary, the order of the priority is C4>C3>C1>C2. With this priority established, the next step involves calculating the weight of the indicators.

Figure 1
Weights MESCA



4.1.2. Analyzing Findings Using SECA Method

Step 1. Formulating the Decision Matrix

The decision matrix within this method takes the form of a row-column matrix. It comprises five research alternatives in rows and ten research criteria in the columns. It is important to note that criteria C5 and C8 possess negative characteristics. Each cell in this matrix serves the purpose of evaluating the alternatives concerning the criteria. Notably, three criteria C1, C6 and C7 have been excluded from the analysis due to identical assessments across the alternatives. These criteria do not involve competitive differentiation among the alternatives.

Step 2. Determining Normalized Values for σj and πj

This section involves the calculation of the normal values for σj and πj, which is accomplished using equations 18 and 19. Normalization is achieved by dividing each πj by the sum of all πj values to obtain normalized values. Fir the normal value of σj, we first calculate the standard deviation (σj). Subsequently, each σj is normalized by dividing it by the sum of the total σj values. The result are presented in Table.6.

Table 6
Normalized Values

πj	σj	Indicators
0/085112	0/190279	C1
0/183476	0/156176	C2
0/183476	0/078088	C3
0/137946	0/078088	C4
0/232768	0/135252	C5
0/092416	0/172659	C6
0/084806	0/189458	C7

Step 3. Optimal Model Results

In this section, we utilize equations 20 to 27 to create and subsequently solve a nonlinear optimization model using Lingo software. Within this model, we have implemented a range of models, varying from 0.1 to 20 for different β values. For each implementation we have determined the weight values of the criteria (denoted as W) and the scores of the alternative (referred to as A). These weight and score values for different β values are presented in Figure 2 and 3. Figures 2 illustrated the evolution of weight values for various β values, ranging from 0.1 to 20, the first index, with a score of 0.111, displays the lowest value.

Figure 2
Changes in the Weight of the Criteria Across Various β Values (SECA)

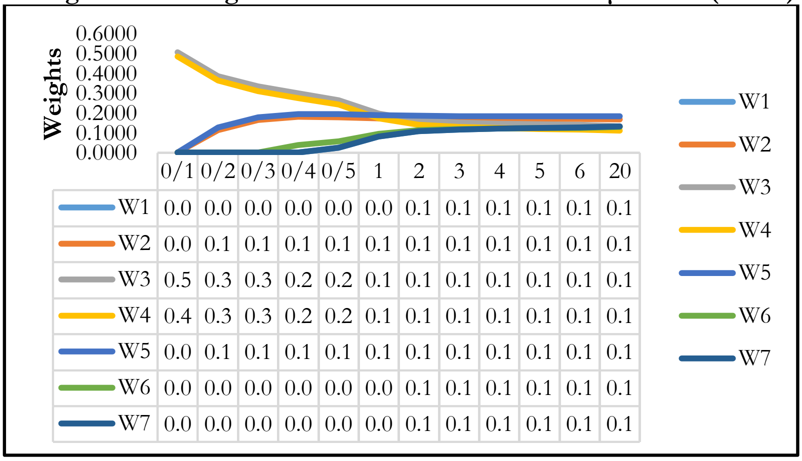


Table 7 below illustrates the ranking of weights for different values of β, starting from 0.1 and continuing up to 20.

Table 7
Rangking in Weights

	β & Rank											
	0/1	**0/2**	**0/3**	**0/4**	**0/5**	**1**	**2**	**3**	**4**	**5**	**6**	**20**
W1	3	5	5	6	6	6	6	6	5	4	4	3
W2	3	4	4	4	4	4	2	2	2	2	2	2
W3	1	1	1	1	1	1	3	3	3	3	3	5
W4	2	2	2	2	2	3	4	4	4	7	7	7
W5	3	3	3	3	3	2	1	1	1	1	1	1
W6	3	5	5	5	5	5	5	5	6	6	6	6
W7	3	5	5	6	6	7	7	7	7	5	5	4

In Figure 3, we observe variations in the available alternatives across a range β values, beginning at 0.1 and extending to 20. As β reaches 20, the second alternative attains the highest score at 0.812, while the third alternative registers the lowest score at 0.513.

Figure 3
Evolution of Alternative Scores Across Various β Values (SECA)

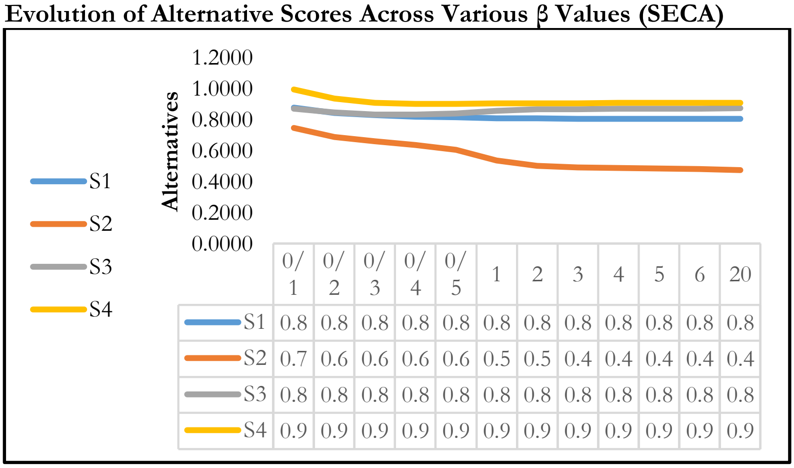


Table 8. displays below, depicts the ranking of weights for a spectrum of β values, commencing at 0.1 and extending to 20.

Table 8

Alternative Rankings (SECA)

	β & Rank											
	0/1	0/2	0/3	0/4	0/5	1	2	3	4	5	6	20
W1	2	3	3	3	3	3	3	3	3	3	3	3
W2	4	4	4	4	4	4	4	4	4	4	4	4
W3	3	2	2	2	2	2	2	2	2	2	2	2
W4	1	1	1	1	1	1	1	1	1	1	1	1

Step 4. Summary of SECA Results

Based on β values greater than 0.1, the prioritization results indicate that the fourth alternative, the Southeast, holds the top ranking with a score of 0.935. Following it, the third alternative, the Southwest, secures the second spot with a score of 0.845. The first alternative, the Northeast, holds the third priority, boasting a score of 0.843. Finally, the second alternative, the Northwest, ranks fourth with a score of 0.687. In summary, the prioritization order is A4> A3> A1> A2.

4.1.3. Comparison of Results for MESCA and SECA Methods

The results revealed that both methods identified the Northwest of East Azerbaijan as the preferred choice for the top priority. Furthermore, there was a congruence in the ranking order between the MESCA and SECA models, as evidenced in Table 9.

Table 9

Comparative Analysis of MESCA and SECA Results

SECA	MESCA	Priority
Southeast	Southeast	1
Southwest	Southwest	2
Northeast	Northeast	3
Northwest	Northwest	4

4.1.4. Determining Suitable City

At this stage, with the Northwest of East Azerbaijan province identified as the top priority, the next step is to determine the specific city where the airport will be situated. In this phase, the cities of Mianeh, Hashtrod and Charavimagh are under consideration for inclusion in the calculations. Other cities have been excluded due to their proximity to Tabriz and shred borders, making them less suitable for the airport location.

4.1.4.1. Formulation of Decision Matrix

Taking into account all the criteria, alternatives, and the assessment of each alternative across various criteria, we have constructed the decision matrix, which is presented in Table 10.

Table 10

Decision Matrix

Attribute / Alternative	1	2	3	4	5	6	7	8	9	10
Charavimagh	29397	453230	V. L.	M	M	V. H.	V. H.	M	L	11
Hashtrod	53576	453230	V. L.	L	M	V. H.	V. H.	H	L	21
Mianeh	180610	453230	M	M	M	V. H.	V. H.	H	M	69

Notes: L= Low; V. L.= Very Low; M= Medium; H= High; and VH= Very High.

Table 11
Normalized Decision Matrix

Attribute / Alternative	1	2	3	4	5	6	7	8	9	10
Charavimagh	453230	29397	1	3	3	5	5	3	2	11
Hashtrod	453230	53576	1	2	3	5	5	2	2	21
Mianeh	453230	180610	3	3	3	5	5	2	3	69

Attribute / Alternative	1	2	3	4	5	6	7	8	9	10	Sum	Mean
Charavimagh	1	0.16	0.33	1	1	1	1	0.67	0.67	0.16	6.98	0.69
Hashtrod	1	0.29	0.33	0.67	1	1	1	1	0.67	0.3	7.26	0.72
Mianeh	1	1	1	1	1	1	1	1	1	1	10	1
Sum	3	1.45	1.67	2.67	3	3	3	2.67	2.33	1.46	24.24	
Mean	1	0.48	0.55	0.88	1	1	1	0.88	0.77	0.48		

$\frac{(\mathbf{vi.})^{ssa} * \mathbf{vi}}{\mathbf{n}} = \overline{\mathbf{vi.}}$ SSA= 0.55 MSA= $9\text{x}10^{-6}$ V1.= 6.98 n= 10

$\frac{2.33^{0.000009} * 2.33}{3} = 0.77$

$\sum_{j=1}^{n}(\mathbf{v..} - \mathbf{vij})^{\mathbf{msa}} = \mathbf{n}$ $(24.25-0.16)^{0.000009}+(24.25-0.29)^{0.000009}+(24.25-1)^{0.000009}=$ m

$(24.25-0.67)^{0.000009}+(24.25-0.67)^{0.000009}+(24.25-1)^{0.000009}=$ 3= m

$\frac{\mathbf{vj.}}{\sum_{i=1}^{m}(\mathbf{v..} - \mathbf{vij})^{\mathbf{msa}}} = \overline{\mathbf{vj.}}$ → $\frac{\mathbf{v1.}}{\sum_{i=1}^{m}(\mathbf{v..} - \mathbf{vij})^{\mathbf{msa}}} = \overline{\mathbf{v1.}}$ $\frac{1.45}{3} = 0.48$

4.1.4.2. Evaluation of Final Results for Both Research Methods

In this phase, we calculate the significance of each alternative based on the methods employed in our research. The outcomes of each method are consolidated and presented in Table 12.

Table 12
Significance of Each Alternative in Both Methods

SECA	MESCA
A1= 0.5286	**C1= 0. 333333251**
A2= 0.5464	**C2= 0. 333333253**
A3= 1	**C3= 0.333333263**

Figure 4 illustrates the weights assigned in the MESCA technique, encompassing all 10 research indicators, however, in Figure 5, we have a refined set of 7 indicators as 3 of them were excluded due to identical values. It's worth noting that the prioritization of alternatives remains consistent in both scenarios, with no discernible distinctions.

Insert Figure 4 and 5 here.

In Figure 6, we observe variations in the weights for a range of β values, commencing from 0.1 and progressing up to 20. When β reaches 20, the 3rd index stands out with the highest score at 0.2275, while the 5th index holds the lowest score at 0.0997.

Figure 4
Weights in MESCA

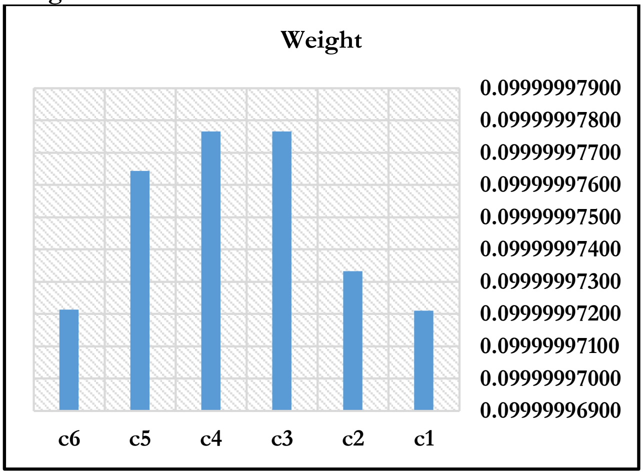


Figure 5
Weights in MESCA without the Same Indicators

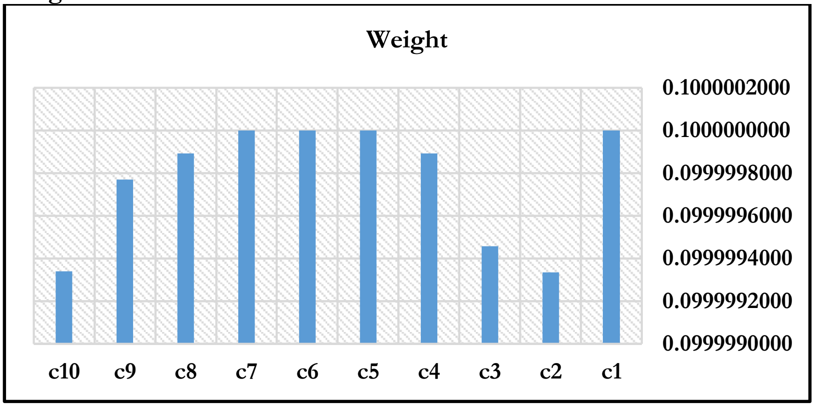


Figure 6
Fluctuations in Criteria Wights Across Various β Values (SECA)

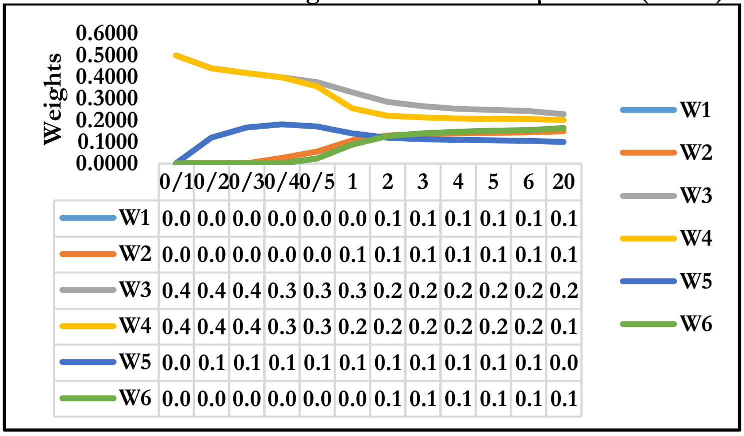


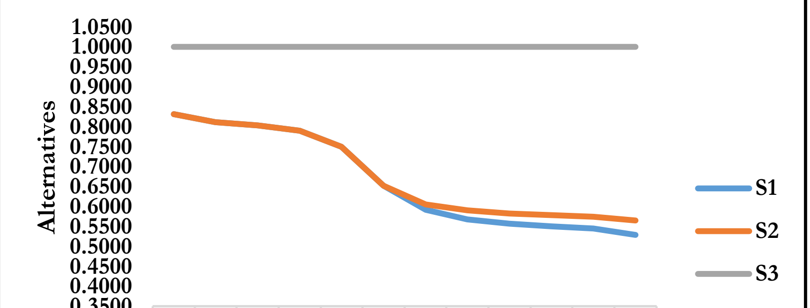
Table 13 provides a comprehensive overview of the weight rankings across spectrum of β values, commencing at 0.1 and extending up to 20.

Table 13
Weight Ranking (SECA)

	β & Rank											
	0/1	**0/2**	**0/3**	**0/4**	**0/5**	**1**	**2**	**3**	**4**	**5**	**6**	**20**
W1	3	4	4	5	6	5	4	3	3	4	3	3
W2	3	4	4	4	4	4	3	5	5	5	5	5
W3	1	1	1	1	1	1	1	1	1	1	1	1
W4	2	2	2	2	2	2	2	2	2	2	2	2
W5	3	3	3	3	3	3	6	6	6	6	6	6
W6	3	4	4	5	5	6	5	4	4	3	4	3

In Figure 7, we observe variations in the alternatives across a range of β values, starting at 0.1 and progressing up to 20. When β reaches 20, the third alternative takes the lead with a score of 1, while the first alternative lags behind with a score of 0.5286. representing the lowest value.

Figure 7
Criteria Weight Dynamics Across Various β Values (SECA)



	0/1	0/2	0/3	0/4	0/5	1	2	3	4	5	6	20
S1	0.8	0.8	0.8	0.7	0.7	0.6	0.5	0.5	0.5	0.5	0.5	0.5
S2	0.8	0.8	0.8	0.7	0.7	0.6	0.6	0.5	0.5	0.5	0.5	0.5
S3	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

Table 14 displays the alternative rankings across a range of β values, commencing at 0.1 and extending up to 20.

Table 14
Eight Ranking (SECA)

	0/1	**0/2**	**0/3**	**0/4**	**0/5**	**1**	**2**	**3**	**4**	**5**	**6**	**20**
S1	2	2	2	2	2	2	3	3	3	3	3	3
S2	2	2	2	2	2	2	2	2	2	2	2	2
S3	1	1	1	1	1	1	1	1	1	1	1	1

4.2. Comparison of MESCA and SECA Research Method

Findings reveal that both methods identify Mianeh as a favourable alternative in the top priority category. Furthermore, notable disparities in prioritization order between MESCA technique and the SECA model are evident, as summarized in Table 15.

Table 15
Priority Comparison of Two Methods

SECA	MESCA	PRIORITY
Mianeh	Mianeh	1
Hashtrod	Hashtrod	2
Charavimagh	Charavimagh	3

4.3. The Chosen Alternative

Miyaneh city, encompassing an expansive area of 5,595 square kilometers (constituting 12.3% of the entire province and serving as its largest city), is strategically positioned 165 kilometers away from Tabriz. It shares its northern borders with Sarab city, while its eastern frontier abuts Ardabil province. To the west, it connects with Bostanabad, Hashtrood, and Charavimaq cities, and to the south, it adjoins Zanjan province. Miyaneh city predominantly experiences a dry and cold climate, except for the lower slopes of the Ghezel Ozan valley in the middle and southeastern parts. The city's elevation varies from 750 meters at the extreme southeast corner of the Ghezel Ozan valley to 3,300 meters at the summit of the Bozqush mountain range. Annual rainfall averages approximately around 320 mm, ranging between 393 and 600 mm in the fluctuating between 393 and 600 mm in the lowlands of the southeast and the higher regions of Bozqush. The average annual temperature in the city ranges from three to 15 degrees Celsius across different areas.

V. CONCLUSION

This study aimed to utilize the MESCA technique for prioritizing available alternatives and compare it with the SECA model in the context of airport selection. To select the most suitable airport, we initially assessed a range of alternatives against crucial criteria spanning aviation, physical attributes, financial considerations, and environmental factors. This multi-criteria assessment aligns with the principles of cost-benefit analysis, a fundamental concept in management accounting. We then subjected these alternatives to a comprehensive comparative analysis, incorporating concepts such as variance analysis and resource allocations, which are vital tools in complex decision-making to determine the best location for airport location.

By juxtaposing the outcomes of the MESCA techniques with those of the SECA model, the strengths of the former approach come to the fore. Notable advantages of the MESCA technique include its simplicity, high precision, flexibility in handling diverse alternatives and indicators, broad applicability across different geographical contexts, cost-effectiveness, and more. These factors that are in alignment with cost management and resource allocation principles in management accounting, are crucial for multidimensional decision making.

The adoption of this method holds considerable promise for organizations and companies grappling with complex decision-making scenarios, where cost analysis and budgetary control play a central role. Furthermore, the applicability of this technique extends beyond airport selection to a wide range of projects, ensuring the identification of the most appropriate alternatives. Our results reveal that both methods yield similar results when it comes to selecting the optimal alternative, in this case with both techniques favoring Mianeh as the top choice based on the specified criteria. In scenarios where discrepancies emerge among alternatives, the MESCA technique proves instrumental, particularly when refinement is required to reinforce confidence in the postponed choice. Employing MESCA techniques not only boosts confidence levels, but also paves the way for enhanced resource allocation and improved financial performance, aligning closely with the fundamental principles of management accounting in across a diverse array of decision-making contexts.

5.1. Suggestions for Future Research

Based on the findings of this study, several avenues of future research can be explored. First, a detailed reevaluation of the airport location in Miyaneh is recommended to precisely identify the optimal site. Further research may involve the integration of additional variables and data sources to enhance the accuracy of this determination.

Second, it is advised to extend the application of MESCA techniques to diverse contexts and decision-making scenarios to validate its reliability and effectiveness when compared to alternative methods. This comparative analysis should be conducted across various industries and sectors to ensure the technique's generalizability.

Third, given the central role of statistical analysis in this methodology, researchers are encouraged to refine and improve statistical techniques to achieve a higher degree of confidence in the results. Developing standardized procedures for applying the MESCA technique can enhance the reliability of its outcomes and facilitate its adoption in decision-making processes.

Lastly, considering that achieving clear convergence in the SECA model can be challenging, particularly when a parameter β is less than 10, it is suggested to explore the application of the β = 6m, where 'm' represents the number of alternatives. This approach has shown consistent positive results in more than 200 practical instances, optimizing both time and financial resources in the decision-making process. Further research in this area can provide valuable insights for improving the practicality of the technique.

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