

Offshoring Location Decision in Fuzzy Environment

Mehmet Şahin^{*,1}

¹Department of Industrial Engineering, Iskenderun Technical University, 31200 Iskenderun, Turkey, mehmet.sahin@simon.rochester.edu, ORCID: 0000-0001-7078-7396

ABSTRACT

Offshoring location selection is a crucial decision for firms in terms of competitiveness, flexibility, productivity, and profitability. Determining an efficient and appropriate location for offshoring has been a substantial multicriteria decision-making (MCDM) problem. Considering that the outcome of an MCDM method alone can be misleading, a novel hybrid approach is presented in this study. Thus, five MCDM methods are utilized to solve the problem, and the results of four MCDM methods are integrated to assure an optimal offshoring location. A Fuzzy-AHP (analytical hierarchy process) integrated with the technique for order preference by similarity to ideal solution (TOPSIS), additive ratio assessment (ARAS), elimination et choix traduisant la réalité (ELECTRE), and weighted sum method (WSM) methodology is proposed for the appraisal and selection of the optimal offshoring location. In this context, fifteen alternative locations are determined based on the attractiveness of the locations in terms of offshoring. Fuzzy-AHP is implemented to analyze the problem's structure and find the weights of the quantitative and qualitative criteria. Consistency tests are implemented to assess the quality of inputs of an expert. Then, TOPSIS, WSM, ARAS, and ELECTRE are used to evaluate and rank the candidate locations and present a comparative analysis. By considering fifteen countries and using real data, offshoring location selection is conducted through the proposed methodology. Moreover, sensitivity analysis is made to diminish the subjectivity and assess the robustness of the techniques. The results demonstrated that giving more weights to the labor characteristics and proximity to market criteria might improve the quality of the best offshoring country index.

ARTICLE INFO

Research article

Received: 17.09.2023

Accepted: 18.03.2024

Keywords:

Offshoring,
decision making,
fuzzy-AHP,
location selection,
comparative analysis.

*Corresponding author

1. Introduction

Offshoring has been one of the most fundamental and significant strategies for manufacturing companies worldwide because of the considerable forces of globalization and competition. It has become one of the most preferred tactics by manufacturing companies to preserve and advance their competitive advantage [1]. Offshoring can be described as the relocation of value-added processes across the national borders of a company [2]. It has the potential to help the firm to obtain the benefits namely lower cost, entering, penetrating, and growth in new markets, flexibility, access to skilled labor, higher productivity in terms of corporate innovativeness, and opportunities to focus on central skills, thus increasing innovation level by offshoring noncore activities [3, 4]. Offshoring is especially widespread in industries (i.e., electronics, auto parts, and machinery), in which manufacturing stages are physically separable, meaning that

they can be made in different locations, and factor intensities vary sharply, meaning that fragmenting manufacture across borders is attractive [5].

Offshoring has become an economic interest, and appealing strategy for the industry worldwide as manufacturing location decision plays a vital role in the performance and future of firms. Thus, the number of studies regarding offshoring has been increasing. In this context, Kinkel and Maloca [6] state that manufacturing offshoring becomes an appealing choice for all-sized firms, mainly due to reduced labor costs. Michel and Rycx [7] examine the effect of offshoring on employment and address that no significant effect of offshoring on Belgium's total employment between 1995 and 2003 is observed. Ellram, Tate [8] use study data to determine the effective criteria for manufacturing location decisions of firms. Stentoft, Mikkelsen [9] evaluate performance outcomes of companies adopting back shoring, staying domestic, and

offshoring and reveal that organizations implementing offshored manufacturing strategy have reduced unit costs compared to companies implementing a staying-at-home strategy.

Location decision-making represents a multi-level hierarchy, in which effective varying parameters exist at each level [10]. This kind of decision requires considerable time and resources, special attention, and thorough data analysis as it involves a high level of uncertainty and impacts the competitiveness and profitability of a firm profoundly [9]. Thus, location decision has attracted considerable interest among practitioners and researchers [11, 12]. Multi-criteria decision-making (MCDM) approaches have been commonly utilized to solve location selection problems. Gupta, Mehlawat [13] present an extended VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) technique for solving a plant location problem. Lai [14] implements integrated simplified swarm optimization with the Analytical Hierarchy Process (AHP) for solving the location problem of the capacitated military logistic depot. Ishizaka, Nemery [15] use the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Weighted Sum Method (WSM), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to determine the ideal location for a casino.

It can be inferred that even though there is an abundant quantity of research on location selection, only a few of them have concentrated on offshoring location selection problems. Liu, Berger [16] apply AHP for offshore outsourcing location decisions. Dou and Sarkis [17] propose an Analytical Network Process (ANP) model for strategic offshoring decisions. López and Ishizaka [18] examine the attributes impacting location criteria (attributes) on offshore outsourcing decisions and their impact on the supply chain resilience capabilities using AHP and fuzzy cognitive maps. De Felice, Petrillo [19] analyze captive offshoring criteria and apply Fuzzy AHP method to obtain the weight of each criterion and sub-criterion. Costanzo and Ahmed [20] propose an offshoring desirability index to determine the value of offshoring locations in the Eastern European. However, the hybridization of successful MCDM methods in the context of evaluating offshoring location decisions is not available in the extant literature except for a study [21]. Thus, addressing this research gap inspires this study to propose a hybrid approach grounded on Fuzzy-AHP with TOPSIS, WSM, additive ratio assessment (ARAS), and elimination et choix traduisant la réalité (ELECTRE) approach to evaluate offshoring location decisions. The reason for choosing these methods is to use different MCDM methods to reveal a practical comparative analysis. Wu, Zhang [22] classify MCDM methods into three types that are outranking (ELECTRE), distance-based (TOPSIS), and utility-based (AHP and WSM) models. Hence, utilizing different methods from different family groups may be valuable. It is the first time to implement all these methods together for this purpose. Also, ARAS is used for offshoring for the first time in this study.

Another inspiration for this study can be explained as follows. A great deal of the studies conducted on offshoring qualitatively examines offshoring from a feasibility perspective and concentrates on reasons for offshoring, advantages, and disadvantages of offshoring, performance improvements, and influencing criteria [23, 24]. However, this study examines the multifaceted "where to offshore" question by implementing quantitative approaches, namely Fuzzy-AHP, TOPSIS, WSM, ARAS, and ELECTRE. It extends the literature in terms of evaluating and comparing different MCDM methods for the "where to offshore" problem. In this context, a novel hybrid approach for offshoring location selection is introduced. Also, a comprehensive analysis is presented.

The chief objective of this study is to reveal a comparative analysis for multicriteria offshoring location selection problems by utilizing Fuzzy-AHP, TOPSIS, WSM, ARAS, and ELECTRE methods. To do so, fifteen countries, which have been commonly preferred for offshoring, are ranked by considering seven main criteria (attributes), namely cost [25, 26], labor characteristics [17, 27], infrastructure [28], proximity to suppliers [29, 30], economic factors [17], quality of life [31], and proximity to market [32, 33] and thirty sub-criteria under these main criteria. These most effective attributes are selected after conducting a comprehensive literature review and utilizing expert knowledge. The criteria weights required by the TOPSIS, WSM, ARAS, and ELECTRE are obtained by utilizing the Fuzzy-AHP. The fifteen alternative countries are evaluated and ranked based on the criteria by TOPSIS, WSM, ARAS, and ELECTRE, respectively. Another reason to adopt more than one MCDM method is that using one MCDM method does not guarantee finding the most suitable solution. Sensitivity analysis is also conducted to minimize the effect of subjective assessments. Thus, a comparative analysis, which contributes to the literature and can be utilized for offshoring and outsourcing decisions, is introduced.

The rest of this research is organized as follows: A brief description of the methods utilized, the methodology and application of the methods, and sensitivity analysis are given in Section 2. In Section 3, the results of the applications and sensitivity analysis and discussions on the results are provided. Finally, the conclusions and possible future studies are presented in Section 4.

2. Materials and Methods

In this study, the Fuzzy-AHP is employed for finding the attribute weights, and TOPSIS, WSM, ARAS, and ELECTRE are used for ranking alternatives to designate the most appropriate offshoring location. The methodology of each method can be described as follows:

2.1. Fuzzy-AHP

The AHP, which was presented by Saaty [34], is capable of tackling complex systems regarding selecting an alternative

from among many candidates and providing a comparison of the considered alternatives. The Fuzzy-AHP is preferred over AHP because of several shortcomings of the AHP. First, the AHP ranking is rather vague. Second, the AHP generates and manages a highly unbalanced judgment scale. Third, the AHP is primarily applied in almost precise decision cases. Fourth, the AHP results are significantly affected by subjective judgment, preference, and selection of decision-makers. Last, the AHP ignores the uncertainty linked with mapping the expert's interpretation of a number [35, 36]. To overcome these shortcomings, an extended form of AHP fuzzy sets can be combined with the pairwise comparison, termed Fuzzy-AHP. The Fuzzy-AHP method permits a more specific explanation of the process of decision-making. This study suggests the use of Fuzzy-AHP for obtaining the criteria weights. The Fuzzy-AHP has been commonly utilized for different problems such as the assessment of solar farms locations [37], location selection for landfill of industrial wastes [38], optimal stock portfolio selection [39], green supply chain management [40], assessment of groundwater potential zones [41], and evaluation of healthcare service quality from the perspective of patients [42]. Even though there are several Fuzzy-AHP methods used in the literature, the Fuzzy-AHP, presented by Chang [43] was utilized in this study due to its computational efficiency and easiness.

Preliminaries:

Let a fuzzy number M on R be a triangular fuzzy number in case its membership function $\mu_M(x): R \rightarrow [0,1]$ is equal to the following equation [43].

$$\mu_M(x) = \begin{cases} \frac{(x-l)}{(m-l)}, & x \in [l, m] \\ \frac{(x-u)}{(m-u)}, & x \in [m, u] \\ 0, & otherwise \end{cases} \quad (1)$$

in which $l \leq m \leq u$, l and u represent the lower and upper value of the support of M , respectively, and m represents the modal value. The triangular fuzzy number may be denoted by (l, m, u) . The operational laws of fuzzy triangular numbers $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ are given in the following equations.

$$(l_1, m_1, u_1) \oplus (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (2)$$

$$(l_1, m_1, u_1) \otimes (l_2, m_2, u_2) \approx (l_1 l_2, m_1 m_2, u_1 u_2) \quad (3)$$

$$(\lambda, \lambda, \lambda) \otimes (l_1, m_1, u_1) = (\lambda l_1, \lambda m_1, \lambda u_1), \quad \lambda > 0, \quad \lambda \in R \quad (4)$$

$$(l_1, m_1, u_1)^{-1} \approx (1/u_1, 1/m_1, 1/l_1) \quad (5)$$

Assuming that an object set is represented by $X = \{x_1, x_2, x_3, \dots, x_n\}$ and a goal set by $U = \{u_1, u_2, u_3, \dots, u_n\}$. Each entity is considered, and extent analysis is made for

every goal (g_i) sequentially. Thus, m extent analysis values for every entity are obtained with the signs:

$$M_{gi}^1, M_{gi}^2, \dots, M_{gi}^m, \quad i = 1, 2, \dots, n \quad (6)$$

in which M_{gi}^j ($j = 1, 2, \dots, m$) are triangular fuzzy numbers. The methodology of the Fuzzy-AHP [43] can be explained in the following steps.

1. The fuzzy synthetic extent value (S_i) regarding the i th entity is represented as:

$$S_i = \sum_{j=1}^m M_{gi}^j \otimes \left[\sum_{i=1}^n \sum_{j=1}^m M_{gi}^j \right]^{-1} \quad (7)$$

To find $\sum_{j=1}^m M_{gi}^j$, the fuzzy addition operation of m extent analysis values for a matrix is applied as follows:

$$\sum_{j=1}^m M_{gi}^j = \left(\sum_{j=1}^m l_j, \sum_{j=1}^m m_j, \sum_{j=1}^m u_j \right) \quad (8)$$

To find $\left[\sum_{i=1}^n \sum_{j=1}^m M_{gi}^j \right]^{-1}$, the fuzzy addition operation of M_{gi}^j ($j = 1, 2, \dots, m$) values is achieved as follows:

$$\sum_{i=1}^n \sum_{j=1}^m M_{gi}^j = \left(\sum_{i=1}^n l_i, \sum_{i=1}^n m_i, \sum_{i=1}^n u_i \right) \quad (9)$$

Next, the inverse of the vector given previously is calculated as follows:

$$\left[\sum_{i=1}^n \sum_{j=1}^m M_{gi}^j \right]^{-1} = \left(\frac{1}{\sum_{i=1}^n u_i}, \frac{1}{\sum_{i=1}^n m_i}, \frac{1}{\sum_{i=1}^n l_i} \right) \quad (10)$$

2. Since $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ are two triangular fuzzy numbers, the possibility degree of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is represented as:

$$V(M_2 \geq M_1) = \sup_{y \geq x} (\min(\mu_{M_1}(x), \mu_{M_2}(y))) \quad (11)$$

and is defined as follows:

$$V(M_2 \geq M_1) = \text{hgt}(M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1 & \text{if } m_2 \geq m_1 \\ 0 & \text{if } l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} & \text{otherwise} \end{cases} \quad (12)$$

This function is illustrated in Figure 1 [44], where d denotes the ordinate of the maximum intersection point D between μ_{M_1} and μ_{M_2} . Both $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ values are needed to compare M_1 and M_2 .

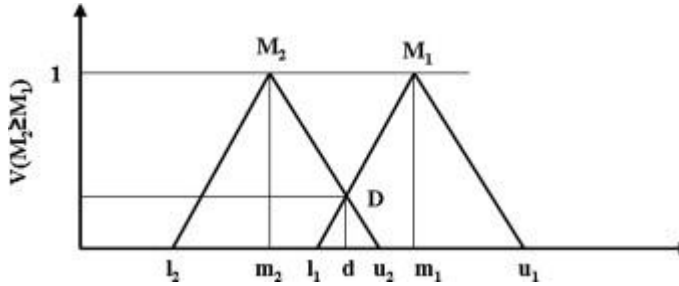


Figure 1. The intersection between M_1 and M_2 [43].

3. For a convex fuzzy number, the possibility degree, to be higher than k convex fuzzy $M_i (i = 1, 2, \dots, k)$ numbers are represented by:

$$\begin{aligned}
 V(M \geq M_1, M_2, \dots, M_k) &= V[(M \geq M_1) \text{ and } (M \\
 &\geq M_2) \text{ and } \dots \text{ and } (M \geq M_k)] \quad (13) \\
 &= \min V(M \geq M_i), i \\
 &= 1, 2, 3, \dots, k
 \end{aligned}$$

Let $d(A_i) = \min V(S_i \geq S_k)$ for $k = 1, 2, \dots, n; k \neq i$. Then the vector of weight is specified by:

$$\hat{W} = (\hat{d}(A_1), \hat{d}(A_2), \dots, \hat{d}(A_n))^T \quad (14)$$

in which $A_i (i = 1, 2, \dots, n)$ are n elements.

4. Through normalization, the normalized weight vectors are:

$$W = (d(A_1), d(A_2), \dots, d(A_n))^T \quad (15)$$

in which W is a non-fuzzy number.

2.2. TOPSIS

The TOPSIS, developed by Hwang and Yoon [45], has been one of the most frequently utilized MCDM methods to determine and rank alternatives for various decision-making problems [46]. It is implemented for location selection problems such as the storage location assignment problem [47], choosing wind farm installation locations [48], optimal solar energy sites identification [49], wave power plant site selection [50], and service apartment location selection [51]. The core principle of the TOPSIS involves selecting the candidate that has the shortest distance from the positive ideal solution (PIS) and the farthest distance from the negative ideal solution (NIS) [45]. It requires limited subjective input from the decision-maker. The structure of the TOPSIS is explained in steps as follows:

Step 1. Forming the evaluation matrix is displayed as follows:

$$\text{Evaluation Matrix} = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \dots & a_{mn} \end{bmatrix} \quad (16)$$

where a_{ij} represents the numerical value collected from the i th option with the j th index.

Step 2. Normalizing the evaluation matrix through the following equation.

$$\begin{aligned}
 r_{ij} &= \frac{a_{ij}}{\sqrt{\sum_{i=1}^m a_{ij}^2}} \quad \text{for } i = 1, 2, \dots, m; j \\
 &= 1, 2, \dots, n
 \end{aligned} \quad (17)$$

Step 3. Determining the weighted normalized decision matrix by using the equation given as follows.

$$v_{ij} = w_j * r_{ij} \quad (18)$$

Step 4. Determining the PIS and NIS for each attribute is as:

$$\text{Positive Ideal Solution} = V_j^+ = \text{MAX}_i(v_{ij}) \quad (19)$$

$$\text{Negative Ideal Solution} = V_j^- = \text{MIN}_i(v_{ij}) \quad (20)$$

Step 5. Computing the geometric distance of each candidate from PIS and NIS through the following functions, respectively.

$$S_i^+ = \sqrt{\sum_{j=1}^n (V_j^+ - v_{ij})^2} \quad (21)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (V_j^- - v_{ij})^2} \quad (22)$$

Step 6. Computing the relative closeness to the ideal solution as:

$$C_i = \frac{S_i^-}{S_i^- + S_i^+} \quad 0 < C_i < 1 \quad (23)$$

The optimal selection is the one that has the maximum relative closeness.

2.3. ELECTRE

ELECTRE was presented by Roy [52]. It is among the most common and effective MCDM methods. ELECTRE III is broadly utilized to deal with ambiguous and uncertain information [53]. Thus, ELECTRE III is adopted for the structure and scope of the present study. It is implemented successfully in tackling MCDM problems such as assessing different kinds of energy generation technologies [54], machine tool remanufacturing [55], optimal site selection [56], autonomous vehicles project [57], site selection for offshore wind power stations [58], and evaluating the optimal location for a construction and demolition waste management facility [59].

The ELECTRE-III method comprises two main phases: forming an outranking association over all the probable candidate pairs and utilizing the outranking association to attain a ranking of the selections in the partial pre-order form [60]. Forming the outranking relation needs the credibility index description that characterizes the credibility of the statement " a outranks b ", aSb , where the index is denoted by $\sigma(aSb)$. It involves the concordance index, $c(aSb)$, and the discordance index for each criterion g_j in F , which is $d_j(aSb)$ [61]. The partial concordance index $c_j(a, b)$ is represented as follows:

$$c_j(a, b) = \begin{cases} 1 & \text{if } g_j(a) \geq g_j(b) - q_j(b) \\ 0 & \text{if } g_j(a) \leq g_j(b) - p_j(b) \\ \frac{g_j(a) - g_j(b) + p_j(b)}{p_j(b) - q_j(b)} & \text{otherwise} \end{cases} \quad (24)$$

The general concordance index is computed for every ordered pair $(a, b) \in A$ as:

$$c(a, b) = \frac{1}{W} \sum_{j=1}^m w_j c_j(a, b) \quad (25)$$

The partial discordance index $d_j(a, b)$ is represented as:

$$d_j(a, b) = \begin{cases} 1 & \text{if } g_j(a) - g_j(b) \leq -v_j(a) \\ 0 & \text{if } g_j(a) - g_j(b) \geq -p_j(a) \\ \frac{g_j(b) - g_j(a) + p_j(a)}{v_j(a) - p_j(a)} & \text{otherwise} \end{cases} \quad (26)$$

Consequently, to attain a valued outranking relation with credibility $\sigma(a, b)$, the general concordance and partial discordance indexes are joined as:

$$\sigma(a, b) = \begin{cases} c(a, b) & \text{if } d_j(a, b) \leq c(a, b), \forall j \\ c(a, b) \cdot \prod_{j \in \bar{F}} \frac{1 - d_j(a, b)}{1 - c(a, b)} & \text{otherwise} \end{cases} \quad (27)$$

where $\bar{F} = \{j \in F : d_j(a, b) > c(a, b)\}$.

2.4. WSM

The WSM has been a reference MCDM method. A score for each alternative A_i is calculated by summing the products of each decision variable with its corresponding criterion weight. The most appropriate alternative that has the highest total score is determined via the following equation.

$$A_i = \sum_{j=1}^n a_{ij} w_j \quad \text{for } i = 1, 2, 3, \dots, m \quad (28)$$

The letters represent the following terms: m : the alternatives; n : the criteria; w_j : the criterion weight; a_{ij} : the score for the i th alternative regarding the j th criterion.

2.5. ARAS

ARAS was presented by Zavadskas and Turskis [62] as a new MCDM method. It is successfully applied to MCDM problems such as evaluation of the blockchain technology strategies [63], evaluation of the e-commerce last-mile logistics' hidden risk hurdles [64], and identification proper process parameters [65]. The procedure of ARAS is described as follows.

Step 1. The decision matrix is normalized through the following equation. The cost attributes are transformed, and then their values are normalized.

$$r_{ij}^* = \frac{r_{ij}}{\sum_{i=0}^m r_{ij}} \quad \text{for } j = 1, 2, \dots, n \quad (29)$$

Step 2. The weighted normalized decision matrix is determined through the following function. The weights of criteria (w_1, w_2, \dots, w_n) are provided by FAHP.

$$\hat{r}_{ij} = r_{ij}^* * w_j \quad \text{for } i = 0, 1, 2, \dots, m \quad j = 1, 2, \dots, n \quad (30)$$

Step 3. The optimality function (S_i) is calculated through the following equation. The higher value indicates the better.

$$S_i = \sum_{j=1}^n \hat{r}_{ij} \quad \text{for } i = 0, 1, 2, \dots, m \quad (31)$$

Step 4. The utility degree is calculated to rank alternatives. The utility degree (k_i) for the i th alternative is calculated through the following equation. The alternative with the highest utility degree is optimal.

$$k_i = \frac{S_i}{V_0} \quad \text{for } i = 0, 1, 2, \dots, m \quad (32)$$

where V_0 is the optimality value of S_i .

2.6. Methodology and Application of the Methods

The framework of the methodology is given in Figure 2. The methodology of the present study and the application of the models can be described as follows. First, a two-level hierarchy of criteria was developed. The first level of the offshoring location evaluation hierarchy consists of seven main criteria: cost, labor characteristics, infrastructure, proximity to suppliers, economic factors, quality of life, and proximity to market. The second level involves thirty sub-criteria under these main criteria (Table 1). All the criteria are determined based on a thorough literature review and expert knowledge.

Then, the Fuzzy-AHP is utilized to obtain the criteria weights since it is commonly used in the literature and provides consistent results. The pairwise comparisons of the criteria are made through the fuzzy scale, as shown in Table 2. The evaluations are provided by an expert decision-maker with twelve years of experience in the field.

The pairwise comparison matrix of the main criteria is given in Table 3. Likewise, the pairwise comparison matrices of all sub-criteria are shown in Table 4.

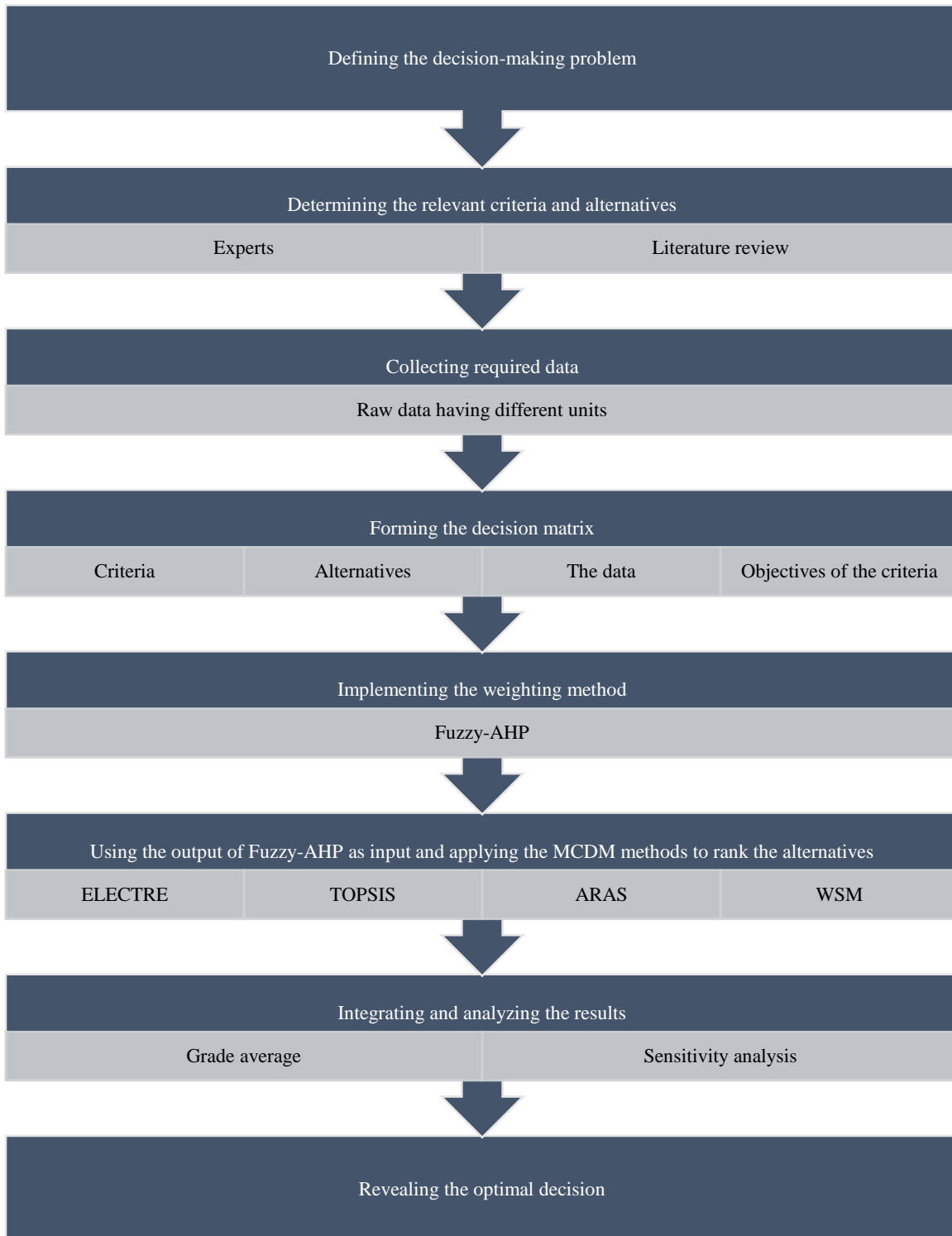


Figure 2. The framework of the methodology.

Table 1. Summary of offshoring location evaluation criteria.

Criteria	Sub-criteria	Description	Objective
Cost (C1)	Cost of labor (C11)	Labor cost	min
	Cost of power (C12)	Electricity rates	min
	Cost of land (C13)	Land cost	min
	Other manufacturing costs (C14)	Cost of starting a business	min
Labor characteristics (C2)	Existence of labor force (C21)	Total labor force	max
	Quality of labor force (C22)	Ease of finding skilled employees	max
	Unemployment rate (C23)	Unemployment rate	min
	Quality of vocational training (C24)	Quality of vocational training	max
Infrastructure (C3)	Existence of airports (C31)	Airport connectivity	max
	Existence of railroads (C32)	Railroad density	max
	Existence of roads (C33)	Road connectivity index	max
	Existence of seaports (C34)	Efficiency of seaport services	max
	Quality and reliability of utilities (C35)	Reliability of water supply	max
	Telecommunication systems (C36)	Percentage of individuals using the internet	max
Proximity to suppliers (C4)	Supplier quality (C41)	Local supplier quality	max
	Supplier quantity (C42)	Local supplier quantity	max
	Existence of international suppliers (C43)	Manufacturing, value added (current US\$)	max
Economic factors (C5)	Tariffs (C51)	Trade tariffs	min
	Inflation (C52)	Inflation annual % change	min
	GDP growth (C53)	GDP growth (annual %)	max
	Income per capita (C54)	Adjusted net national income per capita (current US\$)	max
	Country risk (C55)	Country Risk	min
Quality of life (C6)	Quality of environment (C61)	Pollution index	min
	Climate (C62)	Climate index	max
	Quality of the education system (C63)	Quality of the education system	max
	Health services (C64)	Health index	max
	Crime rate (C65)	Crime index for the country	min
	Standard of living (C66)	Human development index	max
Proximity to markets (C7)	Size of market that can be served (C71)	Population of the country	max
	Population trends (C72)	Population growth rate	max

Table 2. Linguistic scale for the Fuzzy-AHP.

Linguistic variables	Triangular fuzzy scale	Reciprocal of triangular fuzzy scale
Exactly the same	(1, 1, 1)	(1, 1, 1)
Equally important	(0.5, 1, 1.5)	(0.667, 1, 2)
Slightly important	(1, 1.5, 2)	(0.5, 0.667, 1)
Strongly important	(1.5, 2, 2.5)	(0.4, 0.5, 0.667)
Very strongly important	(2, 2.5, 3)	(0.333, 0.4, 0.5)
Extremely important	(2.5, 3, 3.5)	(0.286, 0.333, 0.4)

Table 3. Pairwise comparison concerning goal.

Criteria	C1	C2	C3	C4	C5	C6	C7
C1	(1,1,1)	(1.5,2,2.5)	(1,1.5,2)	(1,1.5,2)	(1,1.5,2)	(2.5,3,3.5)	(2,2.5,3)
C2	(0.4,0.5,0.667)	(1,1,1)	(0.667,1,2)	(0.5,0.667,1)	(0.667,1,2)	(1.5,2,2.5)	(1,1.5,2)
C3	(0.5,0.667,1)	(0.5,1,1.499)	(1,1,1)	(0.5,0.667,1)	(0.667,1,2)	(1,1.5,2)	(0.5,1,1.5)
C4	(0.5,0.667,1)	(1,1.499,2)	(1,1.499,2)	(1,1,1)	(0.5,1,1.5)	(2,2.5,3)	(1.5,2,2.5)
C5	(0.5,0.667,1)	(0.5,1,1.499)	(0.5,1,1.499)	(0.667,1,2)	(1,1,1)	(1,1.5,2)	(0.5,1,1.5)
C6	(0.286,0.333,0.4)	(0.4,0.5,0.667)	(0.5,0.667,1)	(0.333,0.4,0.5)	(0.5,0.667,1)	(1,1,1)	(0.667,1,2)
C7							

C_7 (0.333,0.4,0.5) (0.5,0.667,1) (0.667,1,2) (0.4,0.5,0.667) (0.667,1,2) (0.5,1,1.499) (1,1,1)

Table 4. Pairwise comparison matrices of sub-criteria of cost (a), labor characteristics (b), infrastructure (c), proximity to suppliers (d), economic factors (e), quality of life (f), and proximity to market (g)

(a)

Sub-criteria	C_{11}	C_{12}	C_{13}	C_{14}
C_{11}	(1,1,1)	(1.5,2,2.5)	(1,1.5,2)	(1,1.5,2)
C_{12}	(0.4,0.5,0.667)	(1,1,1)	(0.5,0.667,1)	(0.4,0.5,0.667)
C_{13}	(0.5,0.667,1)	(1,1.499,2)	(1,1,1)	(0.5,0.667,1)
C_{14}	(0.5,0.667,1)	(1.499,2,2.5)	(1,1.499,2)	(1,1,1)

(b)

Sub-criteria	C_{21}	C_{22}	C_{23}	C_{24}
C_{21}	(1,1,1)	(0.667,1,2)	(1,1.5,2)	(1.5,2,2.5)
C_{22}	(0.5,1,1.499)	(1,1,1)	(1,1.5,2)	(1.5,2,2.5)
C_{23}	(0.5,0.667,1)	(0.5,0.667,1)	(1,1,1)	(1,1.5,2)
C_{24}	(0.4,0.5,0.667)	(0.4,0.5,0.667)	(0.5,0.667,1)	(1,1,1)

(c)

Sub-criteria	C_{31}	C_{32}	C_{33}	C_{34}	C_{35}	C_{36}
C_{31}	(1,1,1)	(1.5,2,2.5)	(2,2.5,3)	(0.5,1,1.5)	(2,2.5,3)	(1,1.5,2)
C_{32}	(0.4,0.5,0.667)	(1,1,1)	(0.5,1,1.5)	(0.5,0.667,1)	(1,1.5,2)	(0.5,0.667,1)
C_{33}	(0.333,0.4,0.5)	(0.667,1,2)	(1,1,1)	(0.4,0.5,0.667)	(1,1.5,2)	(0.5,0.667,1)
C_{34}	(0.667,1,2)	(1,1.499,2)	(1.499,2,2.5)	(1,1,1)	(1.5,2,2.5)	(1,1.5,2)
C_{35}	(0.333,0.4,0.5)	(0.5,0.667,1)	(0.5,0.667,1)	(0.4,0.5,0.667)	(1,1,1)	(0.4,0.5,0.667)
C_{36}	(0.5,0.667,1)	(1,1.499,2)	(1,1.499,2)	(0.5,0.667,1)	(1.499,2,2.5)	(1,1,1)

(d)

Sub-criteria	C_{41}	C_{42}	C_{43}
C_{41}	(1,1,1)	(1,1.5,2)	(0.667,1,2)
C_{42}	(0.5,0.667,1)	(1,1,1)	(0.5,0.667,1)
C_{43}	(0.5,1,1.499)	(1,1.499,2)	(1,1,1)

(e)

Sub-criteria	C_{51}	C_{52}	C_{53}	C_{54}	C_{55}
C_{51}	(1,1,1)	(1,1.5,2)	(2,2.5,3)	(1.5,2,2.5)	(0.667,1,2)
C_{52}	(0.5,0.667,1)	(1,1,1)	(1,1.5,2)	(1,1.5,2)	(0.5,0.667,1)
C_{53}	(0.333,0.4,0.5)	(0.5,0.667,1)	(1,1,1)	(0.5,0.667,1)	(0.4,0.5,0.667)
C_{54}	(0.4,0.5,0.667)	(0.5,0.667,1)	(1,1.499,2)	(1,1,1)	(0.5,0.667,1)
C_{55}	(0.5,1,1.499)	(1,1.499,2)	(1.499,2,2.5)	(1,1.499,2)	(1,1,1)

(f)

Sub-criteria	C_{61}	C_{62}	C_{63}	C_{64}	C_{65}	C_{66}
C_{61}	(1,1,1)	(1,1.5,2)	(0.5,1,1.5)	(1.5,2,2.5)	(0.667,1,2)	(0.5,0.667,1)
C_{62}	(0.5,0.667,1)	(1,1,1)	(0.667,1,2)	(0.5,1,1.5)	(0.5,0.667,1)	(0.333,0.4,0.5)
C_{63}	(0.667,1,2)	(0.5,1,1.499)	(1,1,1)	(1,1.5,2)	(0.5,0.667,1)	(0.4,0.5,0.667)
C_{64}	(0.4,0.5,0.667)	(0.667,1,2)	(0.5,0.667,1)	(1,1,1)	(0.4,0.5,0.667)	(0.286,0.333,0.4)
C_{65}	(0.5,1,1.499)	(1,1.499,2)	(1,1.499,2)	(1.499,2,2.5)	(1,1,1)	(0.5,0.667,1)
C_{66}	(1,1.499,2)	(2,2.5,3.3)	(1.499,2,2.5)	(2.5,3.3,3.497)	(1,1.499,2)	(1,1,1)

(g)

Sub-criteria	C_{71}	C_{72}
C_{71}	(1,1,1)	(0.5,1,1.5)
C_{72}	(0.667,1,2)	(1,1,1)

The consistency ratios for the comparison matrices are computed to determine the accuracy of expert assessments.

Once it is assured that the ratio values are accepted values, the subsequent step, in which the alternatives are ranked, is

performed. In this context, fifteen location alternatives, which are Brazil (A1), Canada (A2), Chile (A3), China (A4), Czech Republic (A5), Hungary (A6), India (A7), Malaysia (A8), Mexico (A9), Philippines (A10), Poland (A11), Russia (A12), Singapore (A13), Thailand (A14), and Turkey (A15), are determined based on offshoring location preferences worldwide. The data of each criterion for each country are collected from [66-74]. The data is the input for the TOPSIS, WSM, ARAS, and ELECTRE methods. The alternatives are evaluated against each criterion using the TOPSIS, WSM, ARAS, and ELECTRE methods, for whom the equations mentioned before are employed, respectively. Then, the ranks of alternatives are obtained for each method, and they are compared to each other. Also, an integrated rank of alternatives is presented.

3. Results and Discussion

The Fuzzy-AHP results indicate that the cost criterion has the highest weight, followed by proximity to suppliers, labor characteristics, economic factors, infrastructure, proximity to markets, and quality of life, as shown in Table 5. The consistency ratios of all comparison matrices are less than 10%, which is within a reasonable limit. Table 5 also provides the sub-criteria weights and indicates that labor cost has the highest weight.

Table 5. Weights provided by the Fuzzy-AHP.

Main criteria	Weights of main criteria	Sub-criteria	Local weights of sub-criteria	Global weights of sub-criteria	Rank
C ₁	0.250	C ₁₁	0.386	0.0965	1
		C ₁₂	0.068	0.0170	19
		C ₁₃	0.219	0.0548	5
		C ₁₄	0.328	0.0820	2
C ₂	0.150	C ₂₁	0.339	0.0509	6
		C ₂₂	0.339	0.0509	6
		C ₂₃	0.225	0.0338	14
		C ₂₄	0.097	0.0146	21
C ₃	0.127	C ₃₁	0.299	0.0380	13
		C ₃₂	0.117	0.0149	20
		C ₃₃	0.114	0.0145	22
		C ₃₄	0.259	0.0329	15
		C ₃₅	0.011	0.0014	30
		C ₃₆	0.200	0.0254	17
C ₄	0.197	C ₄₁	0.381	0.0751	3
		C ₄₂	0.237	0.0467	10
		C ₄₃	0.381	0.0751	3
C ₅	0.137	C ₅₁	0.327	0.0448	11
		C ₅₂	0.204	0.0279	16
		C ₅₃	0.043	0.0059	26
		C ₅₄	0.138	0.0189	18
		C ₅₅	0.287	0.0393	12
		C ₅₆	0.011	0.0014	30
C ₆	0.042	C ₆₁	0.198	0.0083	25
		C ₆₂	0.093	0.0039	28
		C ₆₃	0.137	0.0058	27

C ₇	0.095	C ₆₄	0.038	0.0016	29
		C ₆₅	0.208	0.0087	24
		C ₆₆	0.327	0.0137	23
		C ₇₁	0.500	0.0475	8
		C ₇₂	0.500	0.0475	8

To ensure that all criteria can be easily compared concerning the importance levels, the following figure is given. Figure 3 shows that the quality and reliability of utilities is the least important criteria.

Then, the rankings of the offshoring location alternatives are determined through algorithms of TOPSIS, ELECTRE III, ARAS, and WSM methods, as given in Table 6.

Table 6. Rankings of the alternatives by proposed methods.

Alternative	Rankings			
	TOPSIS	ELECTRE III	WSM	ARAS
Brazil	9	13	15	14
Canada	14	1	2	4
Chile	4	9	6	9
China	1	5	1	1
Czech Republic	5	4	4	5
Hungary	7	15	13	15
India	2	6	8	3
Malaysia	6	8	3	11
Mexico	11	2	10	8
Philippines	8	14	11	7
Poland	13	11	7	13
Russia	3	3	9	6
Singapore	15	10	5	2
Thailand	10	12	12	12
Turkey	12	7	14	10

To observe the results clearly and make comparisons, Figure 4 is presented. The TOPSIS results reveal that China is the optimal offshoring location. The ELECTRE results indicate that Canada is the optimal offshoring location. The WSM results reveal that China is the optimal offshoring location. Similarly, the results of the ARAS designate that China is the best option. It is understood that TOPSIS, ARAS, and WSM recommend the same alternative location as the best. This result may indicate that these three methods provide a more consistent result than the ELECTRE, as China has been one of the leading offshoring locations for years. However, this may not be enough to generalize this statement for the whole case. India has also been one of the most preferred offshoring locations. The rankings of India are second, sixth, eighth, and third for TOPSIS, ELECTRE, WSM, and ARAS, respectively. This result indicates that TOPSIS, followed by ARAS, provided a more realistic result than the WSM and ELECTRE. It can also be seen that the ELECTRE ranks India higher than the WSM, meaning that the outcome of the ELECTRE is more realistic for this case. Also, Malaysia, which was ranked third by the WSM, and Mexico, which was

ranked second by the ELECTRE, are two of the most chosen countries for offshoring in real life. Therefore, it can be understood that each method provides effective results for different situations. Considering the overall results of all methods, the Czech Republic is ranked similarly by all the approaches.

To extend the analysis and demonstrate an integrated result, the average ranks of the four methods are calculated and ranked, as shown in Table 7. The integrated results reveal that China is the most suitable offshoring location, followed by the Czech Republic and India. The rank of the Czech Republic might be unexpected. In this regard, to reveal the impact of criteria weights and test the methods' robustness, a sensitivity analysis is conducted.

Table 7. Average ranks of four methods and integrated ranks of alternatives.

Alternative	Average Rank	Integrated Rank
Brazil	12.75	15
Canada	5.25	4
Chile	7	6
China	2	1
Czech Republic	4.5	2
Hungary	12.5	14
India	4.75	3
Malaysia	7	6
Mexico	7.75	8
Philippines	10	10
Poland	11	12

Russia	5.25	4
Singapore	8	9
Thailand	11.5	13
Turkey	10.75	11

As the criteria weights prominently affect the ranking of alternatives, the value change of the weights should be examined. Thus, the impact of subjective evaluation can be observed. Different scenarios are constructed to reveal an overall evaluation. In this context, the main criterion is assigned 90% weight, and the rest 10% of the weight is distributed to the remaining criteria in the ratio of the weights assigned in the beginning. Likewise, the weights of the sub-criteria are allocated in the same way. This process is fulfilled for all criteria, respectively. Additionally, equal weights are assigned to all the criteria as an additional scenario. Sensitivity analysis is performed for the TOPSIS, ELECTRE, ARAS, and WSM methods, so $8 \times 4 = 32$ cases are examined altogether. The results of the calculations are obtained for all methods. The sensitivity analysis outcomes demonstrated that the outcomes of the ELECTRE, ARAS, and WSM are more robust than the TOPSIS, as shown in Table 8. The rankings of these three models are more stable than the TOPSIS as they provide the same rankings under different scenarios. To be noted, scenario "0" represents the original case in this table. Considering all scenarios, it can be inferred that all the approaches provide the closest results in Scenario 5.

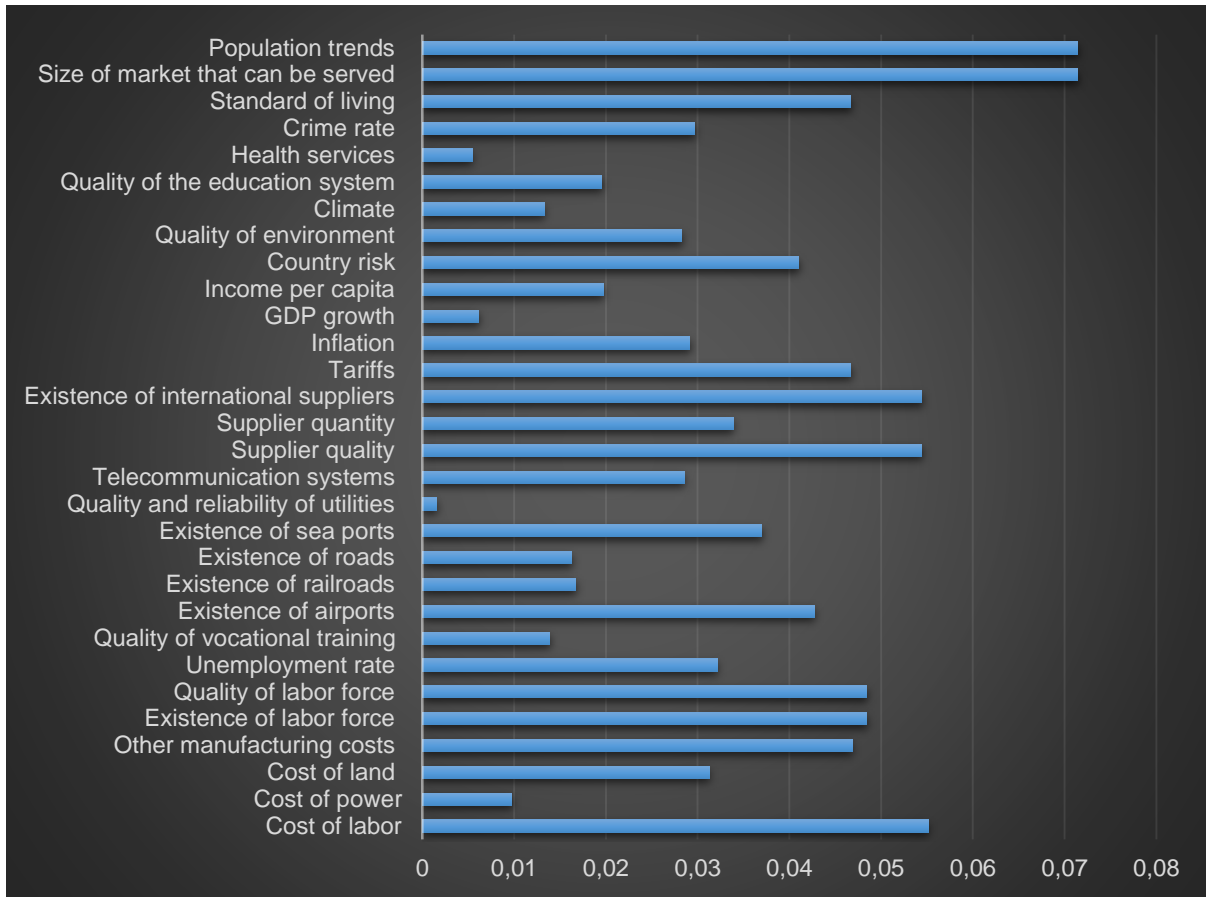


Figure 3. Comparison of weights of criteria.

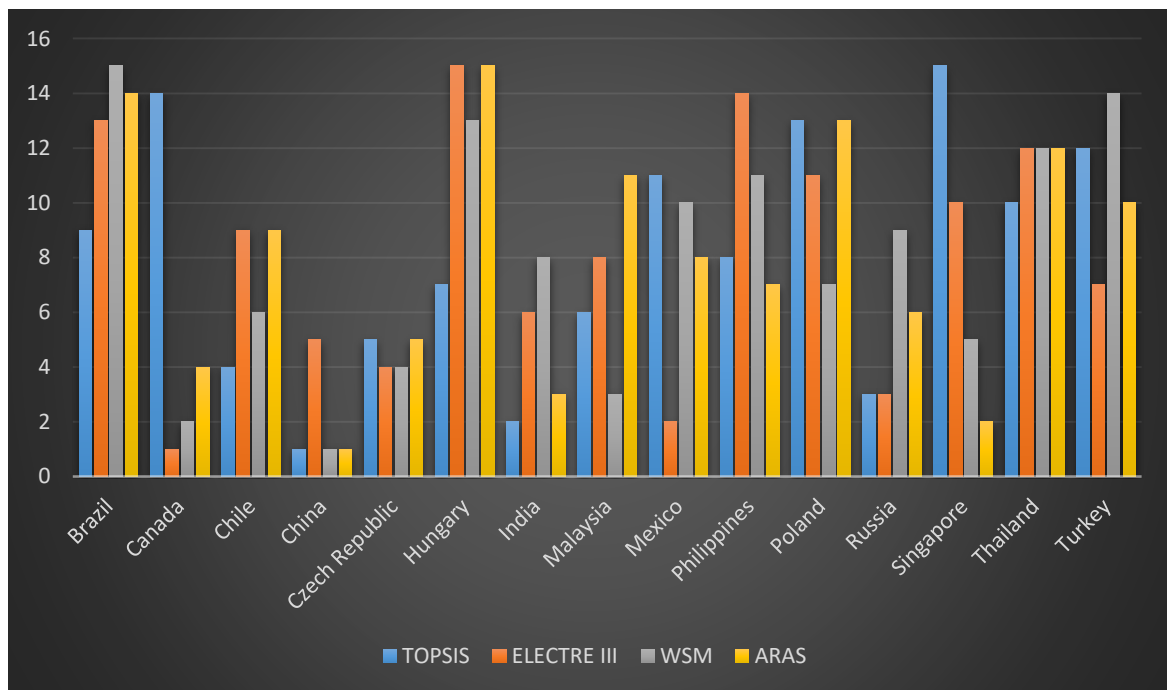


Figure 4. Ranking comparisons of methods.

Table 8. Ranking of locations under different scenarios.

Scenario	Method	Location Ranks														
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15
0	TOPSIS	9	14	4	1	5	7	2	6	11	8	13	3	15	10	12
	WSM	15	2	6	1	4	13	8	3	10	11	7	9	5	12	14
	ELECTRE	13	1	9	5	4	15	6	8	2	14	11	3	10	12	7
	ARAS	14	4	9	1	5	15	3	11	8	7	13	6	2	12	10
1	TOPSIS	3	14	2	8	6	4	11	5	13	12	10	1	15	7	9
	WSM	6	9	3	7	5	4	11	2	13	14	12	1	15	10	8
	ELECTRE	4	2	11	6	14	8	9	3	12	10	13	1	15	7	5
	ARAS	10	1	12	2	8	13	7	11	9	5	15	4	3	14	6
2	TOPSIS	14	12	13	1	7	11	2	5	6	4	10	9	8	3	15
	WSM	15	6	7	1	12	13	2	3	8	5	11	9	4	10	14
	ELECTRE	12	1	10	4	2	14	5	6	3	9	11	8	15	7	13
	ARAS	11	9	13	1	10	15	2	6	7	4	12	8	5	3	14
3	TOPSIS	14	4	12	1	2	5	3	8	11	15	7	10	6	13	9
	WSM	14	3	4	1	5	11	12	7	9	15	6	8	2	13	10
	ELECTRE	12	1	9	8	2	15	11	3	6	14	13	5	4	10	7
	ARAS	14	5	13	1	2	6	4	12	9	15	7	10	3	11	8
4	TOPSIS	7	3	12	1	4	15	2	5	6	14	11	9	10	13	8
	WSM	11	2	7	1	3	15	10	4	8	13	6	12	5	14	9
	ELECTRE	13	1	8	5	4	15	11	7	2	14	10	3	9	12	6
	ARAS	8	3	13	1	6	15	2	7	5	14	11	10	4	12	9
5	TOPSIS	15	2	6	12	3	5	14	7	10	8	4	11	1	9	13
	WSM	15	2	6	10	4	5	13	7	11	8	3	12	1	9	14
	ELECTRE	15	1	3	8	5	7	13	9	10	11	6	4	2	12	14
	ARAS	15	2	6	7	3	5	8	9	13	12	4	10	1	14	11
6	TOPSIS	15	2	10	7	3	4	12	14	11	9	5	8	1	13	6
	WSM	15	2	6	11	3	5	14	8	10	13	4	7	1	12	9
	ELECTRE	13	1	8	10	3	6	15	12	9	11	4	5	2	14	7
	ARAS	15	2	10	4	3	5	9	12	7	13	6	11	1	14	8
7	TOPSIS	8	9	7	2	12	15	1	5	6	3	14	13	10	11	4
	WSM	9	8	6	2	12	15	1	4	7	3	14	13	10	11	5
	ELECTRE	12	3	9	5	4	15	6	8	1	13	10	2	14	11	7
	ARAS	8	9	7	2	13	15	1	5	6	3	14	12	10	11	4
8	TOPSIS	15	6	3	1	8	11	2	4	9	5	12	13	7	14	10
	WSM	15	1	6	2	5	12	7	4	9	11	8	10	3	14	13
	ELECTRE	14	1	9	4	2	15	7	11	3	13	10	5	6	12	8
	ARAS	14	4	6	1	5	15	3	10	7	8	12	11	2	13	9

The changes in the rankings provided by the methods can be observed well in Figure 5. The changes in the ranking of alternatives are seen more often in TOPSIS than the WSM, ARAS, and ELECTRE under different scenarios. This observation can be an indicator of the robustness of the WSM, ARAS, and ELECTRE. However, the results of the TOPSIS suggest China and India as the most optimal offshoring locations, as they are in real life, in several scenarios. Thus, the TOPSIS was distinguished from the WSM and ELECTRE in terms of providing the most realistic outcome for this case. However, all the MCDM approaches suggested in this study provide competitive and effective results.

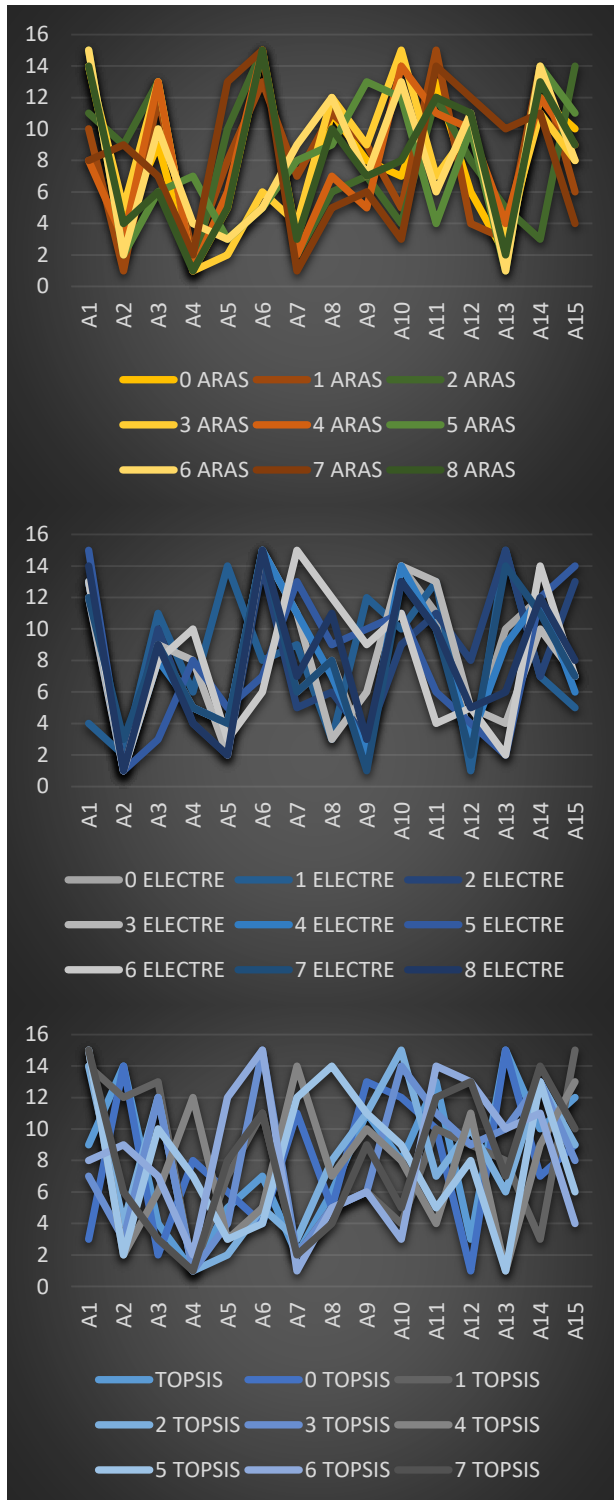


Figure 5. Rank changes of ARAS, ELECTRE, TOPSIS, and WSM.

To sum up, the sensitivity analysis results indicated that the situation in Scenario 2 is close to the case in real life in terms of providing the best offshoring locations, China, and India. It can be inferred that more weights need to be allocated to labor characteristics, namely the existence of labor force, unemployment rate, quality of labor force, and quality of vocational training. Also, Scenario 7 indicated that allocating more weights to proximity to markets criteria, namely the size of market that can be served and population trends, might improve the accuracy of the proposed methodology. Furthermore, if these changes were made, excluding the ELECTRE method might improve the accuracy of the rank result of the integrated rank results.

4. Conclusions

Unlike other studies, this study presented integrated models and a comparative analysis for optimizing decisions of offshoring location that represents a real-life problem. An integrated MCDM-based methodology was proposed for determining the best offshoring location. Thus, a practical approach that can be used by decision-makers in real life was presented. In this context, the Fuzzy-AHP was combined with the TOPSIS, WSM, ARAS, and ELECTRE. Fuzzy-AHP was applied to determine the weights of the criteria obtained from relevant literature and expert knowledge. Then, the alternative offshoring locations were ranked based on TOPSIS, WSM, ARAS, and ELECTRE. ARAS was utilized for the offshoring problem for the first time in this study.

Using actual data, the TOPSIS, WSM, ARAS, and ELECTRE methods provided competitive and effective results for the problem. Moreover, the comparative analysis, which is also a valuable contribution, revealed that the results of the TOPSIS might be assessed as more successful considering the preference rates of the offshoring locations in real life. Additionally, by conducting sensitivity analysis, the robustness of the methods was evaluated, and the subjectivity of evaluations was diminished. The ELECTRE III, ARAS,

and WSM methods were found to be more robust than the TOPSIS as their rankings were more stable compared to the priority ranking in general. However, the TOPSIS was robust in suggesting the best location (A4) in different scenarios. In addition, the results of the sensitivity analysis revealed that allocating more weights to the labor characteristics and proximity to market criteria might improve the quality of the results. Thus, it can be concluded that these methods can be effectively utilized for the offshoring location decision problem. However, the use of ELECTRE might be unnecessary for the purpose of the study if these changes were made. Compared to other studies, MCDM methods were applied to offshoring location selection problems like previous studies. However, the integration of the methods used in this study differs from previous studies.

Subsequently, considerable contributions were made in this study. However, there are some limitations. First, using more MCDM methods could improve the accuracy of the result. Second, implementing objective weighting methods such as entropy and standard deviation might contribute to the analysis. Third, a group decision-making approach could increase reliability. Last, not considering all countries might limit the generalization of the analysis. Thus, future studies can extend the literature by concentrating on utilizing other MCDM methods. Methods of weighting objective criteria for group decision-making can be incorporated into the model. It may also be worth examining more locations and adding additional criteria.

REFERENCES

- [1]. Contractor, F.J., et al. 2010. "Reconceptualizing the Firm in a World of Outsourcing and Offshoring: The Organizational and Geographical Relocation of High-Value Company Functions". *Journal of Management Studies*. **47**(8): p. 1417-1433.
- [2]. Roza, M., F.A.J. Van den Bosch, and H.W. Volberda. 2011. "Offshoring strategy: Motives, functions, locations, and governance modes of small, medium-sized and large firms". *International Business Review*. **20**(3): p. 314-323.
- [3]. Grossman, G.M. and E. Helpman. 2005. "Outsourcing in a Global Economy". *The Review of Economic Studies*. **72**(1): p. 135-159.
- [4]. Mihalache, M. and O.R. Mihalache. 2016. "A Decisional Framework of Offshoring: Integrating Insights from 25 Years of Research to Provide Direction for Future*". *Decision Sciences Journal*. **47**(6): p. 1103-1149.
- [5]. Bergin, P.R., R.C. Feenstra, and G.H. Hanson. 2011. "Volatility due to offshoring: Theory and evidence". *Journal of International Economics*. **85**(2): p. 163-173.
- [6]. Kinkel, S. and S. Maloca. 2009. "Drivers and antecedents of manufacturing offshoring and backshoring—A German perspective". *Journal of Purchasing and Supply Management*. **15**(3): p. 154-165.
- [7]. Michel, B. and F. Rycx. 2011. "Does offshoring of materials and business services affect employment? Evidence from a small open economy". *Applied Economics*. **44**(2): p. 229-251.
- [8]. Ellram, L.M., W.L. Tate, and K.J. Petersen. 2013. "Offshoring and Reshoring: An Update on the Manufacturing Location Decision". *Journal of Supply Chain Management* **49**(2): p. 14-22.
- [9]. Stentoft, J., et al. 2018. "Performance outcomes of offshoring, backshoring and staying at home manufacturing". *International Journal of Production Economics*. **199**: p. 199-208.
- [10]. Schmenner, R.W., J.C. Huber, and R.L. Cook. 1987. "Geographic differences and the location of new manufacturing facilities". *Journal of Urban Economics*. **21**(1): p. 83-104.
- [11]. Buckley, P.J. and M.C. Casson. 2009. "The internalisation theory of the multinational enterprise: A review of the progress of a research agenda after 30 years". *Journal of International Business Studies*. **40**(9): p. 1563-1580.
- [12]. Dunning, J.H. 1998. "Location and the Multinational Enterprise: A Neglected Factor?". *Journal of International Business Studies*. **29**(1): p. 45-66.
- [13]. Gupta, P., M.K. Mehlaawat, and N. Grover. 2016. "Intuitionistic fuzzy multi-attribute group decision-making with an application to plant location selection based on a new extended VIKOR method". *Information Sciences*. **370-371**: p. 184-203.
- [14]. Lai, C.-M. 2019. "Integrating simplified swarm optimization with AHP for solving capacitated military logistic depot location problem". *Applied Soft Computing*. **78**: p. 1-12.
- [15]. Ishizaka, A., P. Nemery, and K. Lidouh. 2013. "Location selection for the construction of a casino in the Greater London region: A triple multi-criteria approach". *Tourism Management*. **34**: p. 211-220.
- [16]. Liu, L.B., et al. 2008. "Applying the analytic hierarchy process to the offshore outsourcing location decision". *Supply Chain Management-an International Journal*. **13**(6): p. 435-449.
- [17]. Dou, Y. and J. Sarkis. 2010. "A joint location and outsourcing sustainability analysis for a strategic offshoring decision". *International Journal of Production Research*. **48**(2): p. 567-592.
- [18]. López, C. and A. Ishizaka. 2017. "A hybrid FCM-AHP approach to predict impacts of offshore outsourcing location decisions on supply chain resilience". *Journal of Business Research*.
- [19]. De Felice, F., A. Petrillo, and L. Petrillo. 2021. "Captive offshoring drivers in the manufacturing industry: criteria and sub-criteria that influence the location choice". *International Journal of Production Research*. **59**(1): p. 76-94.

- [20]. Costanzo, A.M. and S.A. Ahmed. 2021. "Eastern European Offshoring: Determining The Value of Offshoring Locations in Eastern Europe Using Desirability Index". *Performance Improvement*. **60**(4): p. 14-20.
- [21]. Şahin, M. 2020. "Hybrid Multicriteria Group Decision-Making Method for Offshore Location Selection Under Fuzzy Environment". *Arabian Journal for Science and Engineering*.
- [22]. Wu, Y., et al. 2019. "Location selection of seawater pumped hydro storage station in China based on multi-attribute decision making". *Renewable Energy*. **139**: p. 410-425.
- [23]. Johansson, M. and J. Olhager. 2018. "Comparing offshoring and backshoring: The role of manufacturing site location factors and their impact on post-relocation performance". *International Journal of Production Economics*. **205**: p. 37-46.
- [24]. Kaur, H., S.P. Singh, and A. Majumdar. 2019. "Modelling joint outsourcing and offshoring decisions". *International Journal of Production Research*: p. 1-32.
- [25]. Ngwenyama, O.K. and N. Bryson. 1999. "Making the information systems outsourcing decision: A transaction cost approach to analyzing outsourcing decision problems". *European Journal of Operational Research*. **115**(2): p. 351-367.
- [26]. Swenson, D.L. 2005. "Overseas assembly and country sourcing choices". *Journal of International Economics*. **66**(1): p. 107-130.
- [27]. Feldmann, A. and J. Olhager. 2013. "Plant roles: site competence bundles and their relationships with site location factors and performance". *International Journal of Operations & Production Management*. **33**(6): p. 722-744.
- [28]. McMillan, T.E. 1965. "Why Manufacturers Choose Plant Locations vs. Determinants of Plant Locations". *Land Economics*. **41**(3): p. 239-246.
- [29]. Schmenner, R.W., "Making business location decisions". 1982: Prentice Hall.
- [30]. Wheeler, D. and A. Mody. 1992. "International investment location decisions: The case of US firms". *Journal of international economics*. **33**(1-2): p. 57-76.
- [31]. Coughlin, C.C., J.V. Terza, and V. Arromdee. 1991. "State characteristics and the location of foreign direct investment within the United States". *The Review of Economics and Statistics*: p. 675-683.
- [32]. MacCarthy, B.L. and W. Atthirawong. 2003. "Factors affecting location decisions in international operations – a Delphi study". *International Journal of Operations & Production Management*. **23**(7): p. 794-818.
- [33]. Maritan, C.A., T.H. Brush, and A.G. Karnani. 2004. "Plant roles and decision autonomy in multinational plant networks". *Journal of Operations Management*. **22**(5): p. 489-503.
- [34]. Saaty, T.L. 1977. "A scaling method for priorities in hierarchical structures". *Journal of Mathematical Psychology*. **15**(3): p. 234-281.
- [35]. Deng, H. 1999. "Multicriteria analysis with fuzzy pairwise comparison". *International Journal of Approximate Reasoning*. **21**(3): p. 215-231.
- [36]. Wang, T.-C. and Y.-H. Chen. 2007. "Applying consistent fuzzy preference relations to partnership selection". *Omega*. **35**(4): p. 384-388.
- [37]. Asakereh, A., M. Soleymani, and M.J. Sheikhdavoodi. 2017. "A GIS-based Fuzzy-AHP method for the evaluation of solar farms locations: Case study in Khuzestan province, Iran". *Solar Energy*. **155**: p. 342-353.
- [38]. Hanine, M., et al. 2017. "An application of OLAP/GIS-Fuzzy AHP-TOPSIS methodology for decision making: Location selection for landfill of industrial wastes as a case study". *KSCE Journal of Civil Engineering*. **21**(6): p. 2074-2084.
- [39]. Vasantha Lakshmi, K. and K.N. Udaya Kumara. 2024. "A novel randomized weighted fuzzy AHP by using modified normalization with the TOPSIS for optimal stock portfolio selection model integrated with an effective sensitive analysis". *Expert Systems with Applications*. **243**: p. 122770.
- [40]. Dhumras, H. and R.K. Bajaj. 2024. "On potential strategic framework for green supply chain management in the energy sector using q-rung picture fuzzy AHP & WASPAS decision-making model". *Expert Systems with Applications*. **237**: p. 121550.
- [41]. Ally, A.M., et al. 2024. "Assessment of groundwater potential zones using remote sensing and GIS-based fuzzy analytical hierarchy process (F-AHP) in Mpwapwa District, Dodoma, Tanzania". *Geosystems and Geoenvironment*. **3**(1): p. 100232.
- [42]. Singh, A. and A. Prasher. 2019. "Measuring healthcare service quality from patients' perspective: using Fuzzy AHP application". *Total Quality Management & Business Excellence*. **30**(3-4): p. 284-300.
- [43]. Chang, D.-Y. 1996. "Applications of the extent analysis method on fuzzy AHP". *European Journal of Operational Research*. **95**(3): p. 649-655.
- [44]. Zhu, K.-J., Y. Jing, and D.-Y. Chang. 1999. "A discussion on Extent Analysis Method and applications of fuzzy AHP". *European Journal of Operational Research*. **116**(2): p. 450-456.
- [45]. Hwang, C.-L. and K. Yoon, "Methods for multiple attribute decision making", in *Multiple attribute decision making*. 1981, Springer. p. 58-191.
- [46]. Ho, W. and X. Ma. 2018. "The state-of-the-art integrations and applications of the analytic

- hierarchy process". *European Journal of Operational Research*. **267**(2): p. 399-414.
- [47]. Micale, R., C.M. La Fata, and G. La Scalia. 2019. "A combined interval-valued ELECTRE TRI and TOPSIS approach for solving the storage location assignment problem". *Computers & Industrial Engineering*. **135**: p. 199-210.
- [48]. Konstantinos, I., T. Georgios, and A. Garyfalos. 2019. "A Decision Support System methodology for selecting wind farm installation locations using AHP and TOPSIS: Case study in Eastern Macedonia and Thrace region, Greece". *Energy Policy*. **132**: p. 232-246.
- [49]. Jong, F.C. and M.M. Ahmed. 2024. "Novel GIS-based fuzzy TOPSIS and filtration algorithms for extra-large scale optimal solar energy sites identification". *Solar Energy*. **268**: p. 112274.
- [50]. Shao, M., et al. 2024. "A novel framework for wave power plant site selection and wave forecasting based on GIS, MCDM, and ANN methods: A case study in Hainan Island, Southern China". *Energy Conversion and Management*. **299**: p. 117816.
- [51]. Chang, K.-L., et al. 2015. "An ANP based TOPSIS approach for Taiwanese service apartment location selection". *Asia Pacific Management Review*. **20**(2): p. 49-55.
- [52]. Roy, B. 1978. "ELECTRE III: Un algorithme de classements fondé sur une représentation floue des préférences en présence de critères multiples". *Cahiers du CERO*. **20**(1): p. 3-24.
- [53]. Govindan, K. and M.B. Jepsen. 2016. "ELECTRE: A comprehensive literature review on methodologies and applications". *European Journal of Operational Research*. **250**(1): p. 1-29.
- [54]. Martínez-García, M., et al. 2018. "A semantic multi-criteria approach to evaluate different types of energy generation technologies". *Environmental Modelling & Software*. **110**: p. 129-138.
- [55]. Akram, M., F. Ilyas, and M. Deveci. 2024. "Interval rough integrated SWARA-ELECTRE model: An application to machine tool remanufacturing". *Expert Systems with Applications*. **238**: p. 122067.
- [56]. Seyed Alavi, S.M., et al. 2024. "Simultaneous optimal site selection and sizing of a grid-independent hybrid wind/hydrogen system using a hybrid optimization method based on ELECTRE: A case study in Iran". *International Journal of Hydrogen Energy*. **55**: p. 970-983.
- [57]. Akram, M., K. Zahid, and C. Kahraman. 2024. "A new ELECTRE-based decision-making framework with spherical fuzzy information for the implementation of autonomous vehicles project in Istanbul". *Knowledge-Based Systems*. **283**: p. 111207.
- [58]. Wu, Y., et al. 2016. "Study of decision framework of offshore wind power station site selection based on ELECTRE-III under intuitionistic fuzzy environment: A case of China". *Energy Conversion and Management*. **113**: p. 66-81.
- [59]. Baniyas, G., et al. 2010. "Assessing multiple criteria for the optimal location of a construction and demolition waste management facility". *Building and Environment*. **45**(10): p. 2317-2326.
- [60]. Figueira, J.R., et al. 2013. "An Overview of ELECTRE Methods and their Recent Extensions". *Journal of Multi-Criteria Decision Analysis*. **20**(1-2): p. 61-85.
- [61]. Figueira, J., V. Mousseau, and B. Roy, "Electre Methods", in *Multiple Criteria Decision Analysis: State of the Art Surveys*. 2005, Springer New York: New York, NY. p. 133-153.
- [62]. Zavadskas, E.K. and Z. Turskis. 2010. "A new additive ratio assessment (ARAS) method in multicriteria decision-making". *Technological and Economic Development of Economy*. **16**(2): p. 159-172.
- [63]. Hosseini Dehshiri, S.J., M. Amiri, and S.M. Hosseini Bamakan. 2024. "Evaluating the blockchain technology strategies for reducing renewable energy development risks using a novel integrated decision framework". *Energy*. **289**: p. 129987.
- [64]. Raj, R., et al. 2024. "Assessing the e-commerce last-mile logistics' hidden risk hurdles". *Cleaner Logistics and Supply Chain*. **10**: p. 100131.
- [65]. Kannan, S., et al. 2023. "Identification of the effect of strontium and ytterbium addition over magnesium zinc alloy during the drilling process with ARAS and WASPAS techniques". *Materials Chemistry and Physics*. **309**: p. 128320.
- [66]. Global Petrol Prices. 2019 [cited 2019 9/4/2019]; Available from: <https://www.globalpetrolprices.com/>
- [67]. International Telecommunication Union. 2019 [cited 2019 9/4/2019]; Available from: www.itu.int.
- [68]. Numbeo. 2019 [cited 2019 9/4/2019]; Available from: <https://www.numbeo.com>.
- [69]. OECD. 2019 [cited 2019 9/4/2019]; Available from: <http://www.oecd.org/>.
- [70]. United Nations Development Programme. *Human Development Reports*. 2019 [cited 2019 9/4/2019]; Available from: <http://hdr.undp.org/en>.
- [71]. World Bank. 2019 [cited 2019 9/4/2019]; Available from: <https://data.worldbank.org/>.
- [72]. World Data. 2019 [cited 2019 9/4/2019]; Available from: <https://www.worlddata.info/>.
- [73]. World Economic Forum. 2019 [cited 2019 9/4/2019]; Available from: <https://www.weforum.org>.
- [74]. World Population Review. 2019 [cited 2019 9/4/2019]; Available from: <http://worldpopulationreview.com/>.