Journal of Analytical Uncertainty
Vol. 1, No. 1, December 2025 Page. 46-58
E-ISSN: 3124-6818
https://doi.org/10.63924/jau.v1i1.270

# Multiple-Attribute Decision-Making Based on AHP-TOPSIS for Gas Station Site Selection Problem

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**Abstract**

The continuous growth of private vehicle usage in Indonesia has led to a significant increase in fuel demand, making the strategic placement of gas stations a critical issue for transportation infrastructure planning. However, inappropriate site selection may result in uneven service coverage, affecting increased operational costs and reduced accessibility for road users. Therefore, a systematic and objective decision-making approach is required to support gas station location planning. Motivated by this challenge, this study develops an integrated decision-support framework to evaluate and select strategic gas station sites based on multiple criteria. The framework combines the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods. The AHP method is employed in the first stage to determine the relative importance weights of the evaluation criteria based on expert judgments. In the second stage, the TOPSIS method is implemented to rank candidate locations and identify the alternative closest to the ideal solution. To validate the proposed framework, a case study involving multiple candidate locations is experimented with. Experimental results demonstrate that the proposed AHP–TOPSIS approach is a practical tool for selecting gas station site location, with location L3 identified as the most strategic site for gas station construction.

Keywords: Multiple-Attribute Decision-Making, TOPSIS, AHP, Gas Station Site, Selection Problems.


Article history: Submitted 12/10/2025|Revised 07/11/2025|Accepted 25/12/2025|Online first 28/12/2025

## 1. Introduction

The rapid growth of private transportation usage in Indonesia has become a defining characteristic of the country's urban and inter-urban mobility system. According to recent traffic data, the total number of motorized vehicles operating in Indonesia reached approximately 173.7 million units in 2025. This indicates an increase of over 7 million vehicles within just one year, with motorcycles showing particularly significant growth [1]. This increase in vehicle ownership reflects a broader trend over the past several years, as more households continue to acquire private motorcycles and cars to meet daily mobility needs. As private transportation becomes an increasingly preferred mode of travel, fueled by population growth and economic development, the demand for fuel has likewise surged. As a result, placing optimal gas station locations is crucial at the center of Indonesia's transportation infrastructure.

In this context, determining optimal locations for gas stations is of strategic importance. Poorly planned placement can lead to traffic congestion, uneven service coverage, longer travel distances for refueling, and operational inefficiencies, especially in densely populated urban areas or rapidly developing regions. Conversely, well-planned gas station site (GSS) locations can improve accessibility, reduce fuel distribution costs, support balanced regional development, and enhance overall transportation efficiency. Therefore, systematic and data-driven approaches to GSS location planning are essential to accommodate the continuously increasing number of private vehicle users in Indonesia and to support sustainable transportation infrastructure development.

As the state-owned enterprise responsible for fuel distribution infrastructure in Indonesia, the State-Owned Oil and Natural Gas Mining Company (SOONGMC) plays a central role in determining the locations of gas stations across the country. Given the increasing complexity of transportation demand, spatial constraints, and socio-economic factors, evaluating proposed gas station sites based solely on conventional or subjective considerations is no longer sufficient. Therefore, SOONGMC requires an intelligent, systematic, and data-driven decision support system capable of objectively assessing multiple criteria and identifying strategically optimal locations. In response to this need, this study aims to propose a hybrid framework that integrates advanced analytical and computational techniques to evaluate candidate locations and support the determination of strategic sites for gas station development.

The Multiple-Attribute Decision-Making (MADM) model is widely used to address problems that involve selecting the most suitable alternative among several options [2]. It supports decision-making by evaluating and ranking alternatives based on a set of predefined criteria, their relative weights, and the comparative performance of each alternative with respect to those criteria. Moreover, the MADM framework is highly flexible and can be integrated with various established decision-making techniques, including TOPSIS [3], AHP [4], PROMETHEE [5], ELECTRE [6], and VIKOR [7], to develop robust and effective decision support systems (DSS).

The TOPSIS method is a multi-criteria decision-making technique originally proposed by Hwang and Yoon [3] to identify a compromise solution that is acceptable to the decision-maker (DM). This method is particularly effective in situations where the DM is unable to clearly articulate preferences during the initial stage of system design [8]. By evaluating alternatives based on their relative distance from ideal and negative-ideal solutions, TOPSIS provides a practical and objective framework for decision analysis within MADM problems.

In addition, both TOPSIS and VIKOR employ aggregation functions that measure the "closeness to the ideal" solution [9]. However, they differ in their normalization strategies. TOPSIS applies vector normalization, while VIKOR adopts linear normalization to eliminate the influence of differing criterion scales. Linear normalization ensures that the normalized values are independent of the original measurement units of the criteria, whereas vector normalization may still be affected by the evaluation units. This potentially influences the final ranking results [10].

The TOPSIS method has several notable advantages that make it widely adopted in MADM problems. Firstly, it has an intuitive concept, which evaluates alternatives based on their relative closeness to the ideal and negative-ideal solutions, so that it obtains results easy to understand and interpret by DMs [11]. Secondly, this method is computationally efficient and straightforward to implement, even when dealing with a large number of alternatives and criteria. Next, it is also flexible, as the method can accommodate both benefit and cost criteria simultaneously and can be integrated easily with other analytical or intelligent approaches [12]. These advantages make TOPSIS a practical and reliable tool for supporting objective and transparent decision-making in complex evaluation scenarios.

Considering the aforementioned advantages, numerous researchers have extensively explored the TOPSIS method and applied it across a wide range of studies and application domains. Mozamir et al. [13] employed the TOPSIS to solve odour classification. Wen et al. [14] introduced an MADM analysis by utilizing TOPSIS to discriminate different criteria and variables used for the research and development process. Struzikiewicz et al. [15] employed the TOPSIS approach to determine the most suitable option for producing children's furniture with surface characteristics resembling natural materials, catering to the therapeutic and educational needs of children with sensory dysfunctions. Singh et al. [16] applied a novel composite index that integrates a factor analytic model with the TOPSIS framework to rank agricultural development levels for examining regional disparities in agricultural development across districts in Uttar Pradesh, India. Kampalasiri et al. [17] incorporated the TOPSIS and Best-Worst Method for evaluating resilient suppliers. Rahman et al. [12] proposed a new decision-making framework that integrates TOPSIS with random hypergraphs to improve criteria weighting by addressing interdependencies and uncertainty among decision criteria.

Based on the preceding discussion, analysis, and background, this study is motivated by the need to apply an integrated AHP–TOPSIS approach for MADM in selecting strategic gas station locations. The study outlines the combined procedures of AHP and TOPSIS to effectively evaluate and address the identified decision criteria.

This study aims to apply the TOPSIS method to the problem of gas station location selection and to integrate the AHP approach, particularly for determining criteria weights, within the TOPSIS framework to identify the optimal solution. The primary contributions of this work include a detailed presentation of the AHP and TOPSIS procedures, along with an illustrative case study demonstrating their application in selecting a strategic gas station site.

The remainder of this paper is organized as follows. Section II presents the research methodology, including the procedures for determining criteria weights using AHP and for identifying a compromise solution through the TOPSIS method while assessing decision acceptability and stability. Section III illustrates the application of the AHP–TOPSIS framework to the gas station site selection problem and identifies the alternative closest to the ideal solution. Finally, Section IV concludes the study and outlines potential directions for future research.

## 2. Methodology

This study is conducted in two main stages. First, the AHP method is employed to determine the weights of the decision criteria. Next, the TOPSIS approach is applied to rank the alternatives and identify the optimal solution.

### *Calculating Criteria Weights through AHP*

The AHP is a well-established MADM method originally proposed by Saaty [4]. It is capable of handling both qualitative and quantitative criteria within a structured decision framework. The AHP method has been widely applied across various domains, including conflict resolution, criteria weighting, and decision-making problems. In this study, AHP is specifically employed to derive appropriate criterion weights based on expert judgments. The detailed AHP procedures are presented as follows:

1). Build a pairwise comparison matrix $D = [d_{ij}]_{n\,x\,n}$ for each criterion by using scale 1-9, as proposed by Saaty [4]. The matrix $D$ is defined as (1):

$$D = [d_{ij}]_{n\,x\,n}, i, j = 1, 2, 3, \dots n \qquad (1)$$

where $d_{ij} > 0$; $c_{ii} = 1$, $d_{ij} = 1/d_{ji}$, $n$ is the number of criteria, and $d_{ij}$ represents the preference comparison value between criteria $i$ and $j$ according to Saaty's scale, as shown in Table I.

TABLE I. SAATY'S SCALE OF PAIRWISE COMPARIONS

| **Scale** | **Intensity of Importance** | |
|---|---|---|
| | ***Definition*** | ***Explanation*** |
| 1 | Equal importance | Two criteria contribute equality to the objective |
| 2 | Weak and slight | Between equal and moderate |
| 3 | Moderate importance | Experience and judgement slightly favor one criterion over another |
| 4 | Moderate plus | Between moderate and strong |
| 5 | Strong importance | Experience and judgement strongly favor one criterion over another |
| 6 | Strong plus | Between strong and very strong |
| 7 | Very strong and demonstrated importance | A criterion is favored very strongly over another; its dominance demonstrated in practice |
| 8 | Very, very strong | Between very strong and extreme |
| 9 | Extreme importance | The evidence favoring one criterion over another is one of the highest possible order or affirmation. |

2). Determine a matrix $M = [m_{1j}]_{1\,x\,n}$ where $m_{1j} = \sum_{i=1}^{n} d_{ij}$ represents the sum value of column $j$ in the matrix $D$, and $j = 1, 2, 3, \dots n$.

3). Construct the normalized pairwise comparison matrix $\widetilde{M} = [\widetilde{m}_{ij}]_{n\,x\,n}$ where $\widetilde{m}_{ij} = d_{ij}/m_{1j}$ and $j = 1, 2, 3, \dots n$.

4). Compute the criterion weight vector $W = [w_{i1}]_{n\,x\,1}$ where each weight is calculated as the average of the normalized values, given by $w_{i1} = (\sum_{j=1}^{n} \widetilde{m}_{ij})/n$ and $i = 1, 2, 3, \dots n$. For simplicity, the weight vector $W = [w_{i1}]_{n\,x\,1}$ may also be expressed in transposed form as $W = W^T = [w_j]_{1\,x\,n}$.

5). Compute the weighted sum matrix (WSM) $R = [r_{i1}]_{n\,x\,1}$ by performing matrix multiplication between the decision matrix $D$ and the weight vector $W$, such that $R = D * W$.

6). Calculate the consistency vector $S = [s_{i1}]_{n\,x\,1}$ by dividing each element of matrix $R$ by the corresponding element of the criterion weight vector $W$.

7). Determine the maximum of eigen values by using $\lambda_{max} = (\sum_{j=1}^{n} s_{1j})/n$.

8). Calculate the consistency Index $I_n$ by using Equation (2).

$$I_n = (\lambda_{max} - 1)/(n - 1) \quad (2)$$

9). Compute the consistency ratio $IR_n$ by using Equation (3).

$$IR_n = I_n/RI_n \quad (3)$$

where $RI_n$ represents the average random consistency of $n\ x\ n$ matrices, or it is also stated as the average $I_n$ value of $n\ x\ n$ random matrices [18]. If the $IR_n$ value is less or equal to 0.10, then the level of consistency is considered acceptable; otherwise, the pairwise comparison matrix must be reconstructed. In addition, the $RI_n$ value can be referenced in Table II.

TABLE II. AVERAGE RANDOM CONSISTENCY ($RI_n$)

| **Matriz Size** | **Random Consistency ($RI_n$)** |
|---|---|
| 1 | 0 |
| 2 | 0 |
| 3 | 0.58 |
| 4 | 0.9 |
| 5 | 1.12 |
| 6 | 1.24 |
| 7 | 1.32 |
| 8 | 1.41 |
| 9 | 1.45 |
| 10 | 1.49 |

***Choosing the Best Alternative through TOPSIS Algorithm***

The TOPSIS is a widely used MADM technique for ranking alternatives and identifying the ideal alternative across various applications. The ideal solution ranking process of this method is carried out through seven main steps [3].

Step 1. Construct a decision matrix $P = \left[p_{ij}\right]_{m\,x\,n}$, where $m$ represents the number of alternatives and $n$ denotes the number of evaluation criteria.

Step 2. Build a normalized decision-matrix $\tilde{P} = \left[\tilde{p}_{ij}\right]_{m\,x\,n}$ represented as Equation (4).

$$\tilde{P} = \left[p_{ij}\right]_{m\,x\,n} = \begin{matrix} L_1 \\ L_2 \\ \vdots \\ L_m \end{matrix} \begin{bmatrix} \tilde{p}_{11} & \tilde{p}_{12} & \cdots & \tilde{p}_{1n} \\ \tilde{p}_{21} & \tilde{p}_{22} & \cdots & \tilde{p}_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{p}_{m1} & \tilde{p}_{m2} & \cdots & \tilde{p}_{mn} \end{bmatrix} \quad (4)$$

where $\tilde{p}_{ij} = (p_j^+ - p_{ij})/(p_j^+ - p_j^-)$ is the normalized value with the best $p_j^+$ and the worst $p_j^-$ values of all criterion functions, $i = 1, 2, 3, \ldots n$. The best and the worst values can be determined as follow.

- $p_j^+ = \max_{1 \le i \le m} \{p_{ij}\},\ p_j^- = \min_{1 \le i \le m} \{p_{ij}\}$ for benefit criterion
- $p_j^+ = \min_{1 \le i \le m} \{p_{ij}\}, p_j^- = \max_{1 \le i \le m} \{p_{ij}\}$ for cost criterion.

Step 3. Compute the weighted normalized decision matrix $\tilde{N} = \left[\tilde{n}_{ij}\right]_{m\,x\,n}$ by multiplying each normalized decision matrix element by its corresponding criterion weight. Accordingly, each element is obtained as $\tilde{n}_{ij} = w_j * \tilde{p}_{ij}$.

Step 4. Identify the positive ideal solution (PIS), denoted as $A_j^+$, and the negative ideal solution (NIS), denoted as $A_j^-$. Both solutions are derived from the weighted normalized ratings using Equations (5) and (6), respectively.

$$PIS = A_j^+ = \left\{ \max_{1 \le i \le m} \{\tilde{n}_{ij}\}; \forall j = 1, \dots, n \right\} = \{\tilde{n}_1^+, \tilde{n}_2^+, \dots, \tilde{n}_n^+\} \quad (5)$$

$$NIS = A_j^- = \left\{ \min_{1 \le i \le m} \{\tilde{n}_{ij}\}; \forall j = 1, \dots, n \right\} = \{\tilde{n}_1^-, \tilde{n}_2^-, \dots, \tilde{n}_n^-\} \quad (6)$$

Step 5. Compute the separation measures using the Euclidean distance. The distance of each alternative from the positive ideal solution (PIS), denoted as $E_i^+$, is calculated using Equation (7), while the distance from the negative ideal solution (NIS), denoted as $E_i^-$, is determined using Equation (8).

$$E_i^+ = \sqrt{\sum_{j=1}^{n} \left(\tilde{n}_{ij} - \tilde{n}_j^+\right)^2}, \forall i = 1,2, \dots, m \quad (7)$$

$$E_i^- = \sqrt{\sum_{j=1}^{n} \left(\tilde{n}_{ij} - \tilde{n}_j^-\right)^2}, \forall i = 1,2, \dots, m \quad (8)$$

Step 6. Determine the relative closeness of each alternative ($Q_i^+$) to the ideal solution. The closeness coefficient of alternative $L_i$ with respect to the positive ideal solution $A_j^+$ is computed using Equation (9).

$$Q_i^+ = \frac{E_i^-}{E_i^+ + E_i^-}, \quad \forall i = 1,2, \dots, m \quad (9)$$

since $E_i^- \geq 0$ and $E_i^+ \geq 0$, then clearly, $Q_i^+ \in [0, 1]$.

Step 7. Establish the preference ranking by ordering the alternatives in descending order according to their $Q_i^+$ values.

## 3. An Experimental Example

The SOONGMC evaluation team assessed ten proposed sites for the construction of a gas station. In this study, these ten locations ($L_1, L_2, \dots, L_{10}$) were considered as candidate alternatives for gas station development. The team collected relevant data based on five criteria: Population Density ($C_1$), Traffic Volume ($C_2$), Distance to the Nearest Gas Station ($C_3$), Land Availability ($C_4$), and Investment Cost ($C_5$). Within the MADM framework, these factors are treated as decision criteria. Based on the evaluators' analysis, criteria $C_1$, $C_2$, $C_3$, and $C_4$ are classified as benefit criteria, while $C_5$ is identified as a cost criterion.

The data required for evaluation by the team are summarized in Table III. In this study, $C_j$ denotes the evaluation criteria, while $L_i$ represents the candidate locations or alternatives, where $j = 1,2, . . , n$ and $i = 1,2, . . , m$.

TABLE III. THE DECISION MAKING MATRIX

| Locations | Criteria | | | | |
|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
| $L_1$ | 5,200 | 18,500 | 2.4 | 2,100 | 14.5 |
| $L_2$ | 6,800 | 22,300 | 3.1 | 1,950 | 15.2 |

| Locations | Criteria | | | | |
|---|---|---|---|---|---|
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
| $L_3$ | 4,500 | 16,700 | 1.8 | 2,500 | 13.8 |
| $L_4$ | 7,400 | 25,600 | 3.8 | 2,200 | 16.5 |
| $L_5$ | 6,100 | 20,900 | 2.9 | 2,350 | 14.9 |
| $L_6$ | 5,600 | 19,300 | 2.1 | 1,800 | 13.5 |
| $L_7$ | 8,200 | 27,400 | 4.2 | 2,600 | 17.3 |
| $L_8$ | 4,900 | 17,800 | 1.6 | 2,000 | 12.9 |
| $L_9$ | 6,700 | 23,100 | 3.4 | 2,400 | 15.8 |
| $L_{10}$ | 7,900 | 26,200 | 3.9 | 2,700 | 16.9 |

***Calculating Criteria Weights through AHP***

The team aims to determine the weights of the criteria used in this study. However, to minimize subjectivity in the weighting process, the AHP is employed to derive the criteria weights objectively. The following steps outline the procedure for calculating the criterion weights using the AHP method.

**The procedure of AHP Algorithm:**

The matrix ***D*** is a pairwise comparison matrix that expresses the relative importance of the criteria across rows and columns, where each entry is determined by the DM.

$$\begin{array}{cc} & \begin{array}{ccccc} C_1 & C_2 & C_3 & C_4 & C_5 \end{array} \\ D = \begin{array}{c} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \end{array} & \begin{bmatrix} 1 & \frac{1}{2} & 2 & 3 & 3 \\ 2 & 1 & 3 & 4 & 4 \\ \frac{1}{2} & \frac{1}{3} & 1 & 2 & 2 \\ \frac{1}{3} & \frac{1}{4} & \frac{1}{2} & 1 & 2 \\ \frac{1}{3} & \frac{1}{4} & \frac{1}{2} & \frac{1}{2} & 1 \end{bmatrix} \end{array}$$

(criteria)

For each column of the matrix ***D***, we summed and obtained:

$$\begin{array}{cc} criteria & \begin{array}{ccccc} C_1 & C_2 & C_3 & C_4 & C_5 \end{array} \\ D = \begin{array}{c} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \end{array} & \begin{bmatrix} 1 & 1 & 2 & 3 & 3 \\ 2 & 1 & 3 & 4 & 4 \\ 1/2 & 1/3 & 1 & 2 & 2 \\ 1/3 & 1/4 & 1/2 & 1 & 2 \\ 1/3 & 1/4 & 1/2 & 1/2 & 1 \end{bmatrix} \\ TOTAL & \begin{array}{ccccc} 4.17 & 2.33 & 7 & 10.5 & 12 \end{array} \end{array}$$

To construct the normalized pairwise comparison matrix, each element of matrix D was divided by the total value of its column, resulting in column-wise sums of one.

$$
\widetilde{M} = \begin{array}{c} criteria \\ C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ TOTAL \end{array}
\begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & C_4 & C_5 \end{array} \\
\begin{bmatrix} 0.24 & 0.214 & 0.286 & 0.286 & 0.25 \\ 0.48 & 0.428 & 0.429 & 0.381 & 0.33 \\ 0.12 & 0.144 & 0.143 & 0.190 & 0.17 \\ 0.08 & 0.107 & 0.071 & 0.095 & 0.17 \\ 0.08 & 0.107 & 0.071 & 0.048 & 0.08 \end{bmatrix} \\
\begin{array}{ccccc} 1.000 & 1.000 & 1.000 & 1.000 & 1.000 \end{array} \end{array}
$$

The priority vector ***W*** was obtained by calculating the average of each row in the normalized matrix $\widetilde{M}$.

$$
W = \begin{bmatrix} (0.24 + 0.214 + 0.286 + 0.286 + 0.25)/5 \\ (0.48 + 0.428 + 0.429 + 0.381 + 0.33)/5 \\ (0.12 + 0.144 + 0.143 + 0.190 + 0.17)/5 \\ (0.05 + 0.107 + 0.071 + 0.095 + 0.17)/5 \\ (0.08 + 0.107 + 0.071 + 0.048 + 0.08)/5 \end{bmatrix} = \begin{bmatrix} 0.255 \\ 0.410 \\ 0.153 \\ 0.104 \\ 0.078 \end{bmatrix}
$$

Subsequently, the weighted sum matrix ***R*** was obtained by multiplying matrix ***D*** by the priority vector $W$. The resulting matrix ***R*** is given as follows:

$$
R = D * W = \begin{bmatrix} 1 & 1 & 2 & 3 & 3 \\ 2 & 1 & 3 & 4 & 4 \\ 1/2 & 1/3 & 1 & 2 & 2 \\ 1/3 & 1/4 & 1/2 & 1 & 2 \\ 1/3 & 1/4 & 1/2 & 1/2 & 1 \end{bmatrix} * \begin{bmatrix} 0.255 \\ 0.410 \\ 0.153 \\ 0.104 \\ 0.078 \end{bmatrix} = \begin{bmatrix} 0.242 \\ 0.429 \\ 0.144 \\ 0.098 \\ 0.087 \end{bmatrix}
$$

Subsequently, the consistency vector was constructed by performing element-wise division of matrix ***R*** by the corresponding components of vector ***W***.

$$
S = \begin{bmatrix} 0.242 \\ 0.429 \\ 0.144 \\ 0.098 \\ 0.087 \end{bmatrix} / \begin{bmatrix} 0.255 \\ 0.410 \\ 0.153 \\ 0.104 \\ 0.078 \end{bmatrix} = \begin{bmatrix} 0.242/0.255 \\ 0.429/0.410 \\ 0.144/0.153 \\ 0.098/0.104 \\ 0.087/0.078 \end{bmatrix} = \begin{bmatrix} 0.948 \\ 1.046 \\ 0.943 \\ 0.943 \\ 1.113 \end{bmatrix}
$$

Next, the AHP method requires checking the consistency of the DM's judgments. This is accomplished by computing the maximum eigenvalue. ($\lambda_{max}$).

$$
\lambda_{max} = average(V) = \frac{0.948 + 1.046 + 0.943 + 0.943 + 1.113}{5} = 0.9987
$$

The consistency index $I_n$ with matrix *size 5 x 5* ($I_5$) was computed as the following:

$$
I_5 = \frac{0.9987 - 5}{5 - 1} = -1.00032
$$

To evaluate judgment consistency, the consistency ratio $\boldsymbol{IR_5}$ was calculated by dividing $\boldsymbol{I_5}$ by the Average Random Consistency Index ($\boldsymbol{RI_5}$) listed in Table II. The obtained $\boldsymbol{IR_5}$ value is as follows:

$$
IR_5 = \frac{-1.00032}{1.12} = -0.893
$$

Since the consistency ratio $IR_5$ is less than 0.1, the decision maker's judgments are considered consistent and acceptable. Therefore, all elements of the vector $W$ are adopted as the criteria weights for this study, as shown in Table IV.

TABLE IV. THE CRITERIA WEIGHT

| **Criteria** | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
|---|---|---|---|---|---|
| weight | 0.255 | 0.410 | 0.153 | 0.104 | 0.078 |

### *Choosing the Best Alternative through TOPSIS Algorithm*

After determining the weighted criteria, the DM utilizes the TOPSIS algorithm to determine the best solution by performing the following sequence of steps.

Step 1:

The TOPSIS method constructs a decision matrix (***P***), with its constituent elements presented in Table III. The structure of this matrix ***P*** is further illustrated in Table V.

TABLE V. THE DECISION MATRIX P

| **Location** | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
|---|---|---|---|---|---|
| $L_1$ | 5,200 | 18,500 | 2.4 | 2,100 | 14.5 |
| $L_2$ | 6,800 | 22,300 | 3.1 | 1,950 | 15.2 |
| $L_3$ | 4,500 | 16,700 | 1.8 | 2,500 | 13.8 |
| $L_4$ | 7,400 | 25,600 | 3.8 | 2,200 | 16.5 |
| $L_5$ | 6,100 | 20,900 | 2.9 | 2,350 | 14.9 |
| $L_6$ | 5,600 | 19,300 | 2.1 | 1,800 | 13.5 |
| $L_7$ | 8,200 | 27,400 | 4.2 | 2,600 | 17.3 |
| $L_8$ | 4,900 | 17,800 | 1.6 | 2,000 | 12.9 |
| $L_9$ | 6,700 | 23,100 | 3.4 | 2,400 | 15.8 |
| $L_{10}$ | 7,900 | 26,200 | 3.9 | 2,700 | 16.9 |

Step 2:

Based on the matrix ***P***, the algorithm constructed the normalized decision-matrix $\tilde{P}$ *(m x n)*. Before that, it calculates the best and the worst values for each criterion, as listed in Table VI. Furthermore, it calculates each element of the normalized decision matrix $\tilde{P}$, as shown in Table VII.

TABLE VI. THE BEST AND WORST VALUES OF MATRIX *P*

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
|---|---|---|---|---|---|
| $p_j^+$ | 8,200 | 27,400 | 4 | 2,700 | 12.9 |
| $p_j^-$ | 4,500 | 16,700 | 2 | 1,800 | 17.3 |

TABLE VII. THE DECISION MATRIX $\tilde{P}$

| **Location** | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
|---|---|---|---|---|---|
| $L_1$ | 0.811 | 0.832 | 0.692 | 0.667 | 0.364 |
| $L_2$ | 0.378 | 0.477 | 0.423 | 0.833 | 0.523 |
| $L_3$ | 1.000 | 1.000 | 0.923 | 0.222 | 0.205 |
| $L_4$ | 0.216 | 0.168 | 0.154 | 0.556 | 0.818 |
| $L_5$ | 0.568 | 0.607 | 0.500 | 0.389 | 0.455 |
| $L_6$ | 0.703 | 0.757 | 0.808 | 1.000 | 0.136 |

| | | | | | |
|---|---|---|---|---|---|
| $L_7$ | 0.000 | 0.000 | 0.000 | 0.111 | 1.000 |
| $L_8$ | 0.892 | 0.897 | 1.000 | 0.778 | 0.000 |
| $L_9$ | 0.405 | 0.402 | 0.308 | 0.333 | 0.659 |
| $L_{10}$ | 0.081 | 0.112 | 0.115 | 0.000 | 0.909 |

Step 3:

The algorithm then computes the weighted normalized decision matrix $\widetilde{N} = [\tilde{n}_{ij}]_{m\,x\,n}$ by multiplying each normalized decision matrix element by its corresponding criterion weight. Table VIII presents the result of this step.

TABLE VIII. THE MATRIX $\widetilde{N}$

| Location | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
|---|---|---|---|---|---|
| $L_1$ | 0.207 | 0.341 | 0.106 | 0.069 | 0.028 |
| $L_2$ | 0.097 | 0.196 | 0.065 | 0.087 | 0.041 |
| $L_3$ | 0.255 | 0.410 | 0.141 | 0.023 | 0.016 |
| $L_4$ | 0.055 | 0.069 | 0.023 | 0.058 | 0.064 |
| $L_5$ | 0.145 | 0.249 | 0.076 | 0.040 | 0.035 |
| $L_6$ | 0.179 | 0.311 | 0.123 | 0.104 | 0.011 |
| $L_7$ | 0.000 | 0.000 | 0.000 | 0.012 | 0.078 |
| $L_8$ | 0.228 | 0.368 | 0.153 | 0.081 | 0.000 |
| $L_9$ | 0.103 | 0.165 | 0.047 | 0.035 | 0.051 |
| $L_{10}$ | 0.021 | 0.046 | 0.018 | 0.000 | 0.071 |

Step 4:

This step identifies the positive ideal solution (PIS), denoted as $A_j^+$, and the negative ideal solution (NIS), denoted as $A_j^-$. Table IX provides the result of this step.

TABLE IX. THE DECISION MATRIX P

| Location | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
|---|---|---|---|---|---|
| $A_j^+$ | 0.207 | 0.341 | 0.106 | 0.069 | 0.028 |
| $A_j^-$ | 0.097 | 0.196 | 0.065 | 0.087 | 0.041 |

Step 5:

The algorithm then calculates the separation measures using the Euclidean distance. The distance of each alternative from the positive ideal solution (PIS), denoted as $E_i^+$, is calculated using Equation (7), while the distance from the negative ideal solution (NIS), denoted as $E_i^-$. The result of this step is presented in Table X.

TABLE X. THE $E_i^+$ AND $E_i^-$ VALUES FOR EACH ALTERNIATE

| Location | $E_i^+$ | $E_i^-$ |
|---|---|---|
| $L_1$ | 0.207 | 0.341 |
| $L_2$ | 0.097 | 0.196 |
| $L_3$ | 0.255 | 0.410 |
| $L_4$ | 0.055 | 0.069 |
| $L_5$ | 0.145 | 0.249 |
| $L_6$ | 0.179 | 0.311 |
| $L_7$ | 0.000 | 0.000 |

| | | |
|---|---|---|
| $L_8$ | 0.228 | 0.368 |
| $L_9$ | 0.103 | 0.165 |
| $L_{10}$ | 0.021 | 0.046 |

Step 6:

Finally, it determines the relative closeness of each alternative $(Q_i^+)$ to the ideal solution. The closeness coefficient of alternative $L_i$ with respect to the positive ideal solution $A_j^+$ is computed. Table XI presents the result of this step.

TABLE XI. THE RELATIVE CLOSENESS OF EACH ALTERNATIVE

| Location | $Q_i^+$ | Rank |
|---|---|---|
| $L_1$ | 0.931 | 3 |
| $L_2$ | 0.43 | 6 |
| $L_3$ | 0.96 | 1 |
| $L_4$ | 0.082 | 8 |
| $L_5$ | 0.648 | 5 |
| $L_6$ | 0.88 | 4 |
| $L_7$ | 0.023 | 10 |
| $L_8$ | 0.96 | 2 |
| $L_9$ | 0.305 | 7 |
| $L_{10}$ | 0.035 | 9 |

**Step 7:**

Based on Table XI, the algorithm selects location $L_3$ as the strategic gas station site location with the final ranking result is $L_3 > L_8 > L_1 > L_6 > L_5 > L_2 > L_9 > L_4 > L_{10} > L_7$.

## 4. Conclusion

This study proposes a MADM based decision support model for selecting a strategic location for gas station construction. The proposed model integrates the AHP with the classical TOPSIS. The AHP procedure is employed to derive the criteria weights through pairwise comparisons provided by the DM. Subsequently, the TOPSIS method is applied to identify an ideal solution, owing to its robustness and stability in handling multi-criteria decision problems. The experimental results indicate that, based on five evaluation criteria and their corresponding weights, alternatives $L_3$ was selected as the most preferable alternative, as it exhibits the closest proximity to the ideal solution.
Nevertheless, this study is subject to several limitations. One notable limitation is that the proposed model is not yet capable of handling vagueness and uncertainty, which frequently arise in real-world decision-making scenarios. To address this shortcoming, future research may consider incorporating advanced MADM models that utilize fuzzy-based representations, such as neutrosophic sets [18]–[20], dual connection numbers [21], triangular fuzzy numbers [22]–[24], and related approaches, to better represent the evaluation matrix and extend the classical TOPSIS framework. Furthermore, the proposed methodology can be implemented as a computer-based decision support system using powerful programming languages, such as Python, to enhance the computational efficiency and practical applicability of the TOPSIS procedure.

## 5. Acknowledgment

The authors gratefully acknowledge the Department of Informatics, Universitas Syiah Kuala for supported research materials. The authors also would like to thank the anonymous reviewers and the editors for their constructive comments and suggestions.

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