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Min–Max Fuzzy TOPSIS with Entropy Weighting for Strategic Location Multicriteria Decision Making

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ABSTRACT

This study aimed to develop a robust, objective framework for strategic location Multicriteria Decision Making (MCDM) by effectively addressing criteria conflict and data uncertainty. The research methodology utilized a novel hybrid approach, integrating the Entropy method to determine objective criteria weights with a Min-Max Fuzzy TOPSIS model, a modification adopted specifically to improve the consistency and rationality of alternative ranking results. The model was applied to a case study concerning strategic location selection in Batubara Regency, evaluating five alternative locations based on six criteria. The major finding from the objective weighting process was that the Number of Students (Crt_2) was the most influential criterion, receiving the highest weight of 0.294. Subsequent analysis using the modified Fuzzy TOPSIS revealed that Alternative Alt_1 (Madang Deras) achieved the highest performance index $(Alt_1^* = 0.673)$, securing the first rank. Numerical validation showed a significant improvement over existing approaches. When compared with the original Min-Max Fuzzy TOPSIS, the Performance Index of the best alternative (Alt_1) increased from 0.588 to 0.673, representing a 14.46% improvement. Furthermore, when evaluated against a model using uniform weighting, the Performance Index increased from 0.449 to 0.673, reflecting a substantial 49.89% enhancement. These results demonstrate that entropy-based objective weighting meaningfully improves the discriminative power of the decision model and reduces bias. Overall, the proposed hybrid framework offers a more stable, accurate, and comprehensive approach for strategic location selection.

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1. INTRODUCTION

Selecting a strategic location is a key decision in development planning, as it has long-term impacts and involves significant capital investment. Mistakes in selecting a location risk high operational costs, limited access, and failure to achieve project objectives. The significance of this decision is evident in various contexts, from selecting the optimal location for a sustainable MSME development center [1], to efficient campuses [2], to energy infrastructure [3]. More broadly, the strategic importance of location is further highlighted in critical areas such as warehouse selection in supply chain management [4] and the selection of sustainable hub locations for logistics distribution [5].

The problem of location selection is becoming increasingly important and complex, particularly in supporting national-scale government programs, such as the selection of rice industry locations for the Makan Bergizi Gratis (MBG) initiative. This decision requires evaluating potential sites by considering various, often conflicting, criteria, such as rice production, road conditions, and average travel time. Furthermore, location evaluation also suffers from uncertainty (fuzziness), particularly when criteria are assessed using ambiguous linguistic terms. To handle this vagueness, Triangular Fuzzy Numbers (TFN) are widely employed in MCDM as a practical tool to represent linguistic uncertainty in expert evaluation [6] and to model human decision-making, such as regret aversion [7].

Previous research [2] has shown that strategic location selection has not integrated objective entropy weighting with Fuzzy TOPSIS using Min–Max operations, even though this combination is important to address data complexity and uncertainty. The need for this modification stems from known methodological issues; for example, conventional TOPSIS methods are known to be susceptible to rank reversals (changes in ranking order) depending on the choice of distance metric and the normalization method used [8]. Modifications to the normalization step have been shown to improve the robustness of TOPSIS rankings to data fluctuations [9], and efforts to develop MCDM techniques that go beyond classical consistency are a recent methodological research trend [10].

To fill this methodological gap, the current research presents a hybrid solution that integrates the Entropy Method and Fuzzy TOPSIS adapted with Min–Max operation. The Entropy Method serves to objectively assign criteria weights, ensuring the most informative and unique criteria receive higher weights and reducing subjectivity [11]. This objective weighting approach is critical, as studies confirm that combining objective Entropy and subjective weights provides a more rational and fair evaluation [12]. Simultaneously, Fuzzy TOPSIS addresses the inherent uncertainty in linguistic criteria evaluation.

A significant contribution of this study is the novel integration of the Min-Max operation into the standard Fuzzy TOPSIS methodology. Mathematically, the Min-Max operation improves ranking consistency by using the strict conjunction operator (Min) when measuring proximity to the Positive Ideal Solution (PIS), which effectively limits the overall proximity to the lowest performer, thus creating higher discrimination power and more rational and logical ranking results. This modification is implemented to improve the consistency and rationality of alternative ranking results, specifically addressing the inherent ambiguity and data variation in the decision-making process. Given the known vulnerability of TOPSIS to ranking reversals caused by model modifications or alternative downgrading [13], it is important to emphasize that the stability and validity of ranking results must be ensured through sensitivity analysis [14]. By combining objective weighting derived from the Entropy method that takes into account data uncertainty and the new Min-Max optimized Fuzzy TOPSIS ranking, the proposed framework is able to handle multi-criteria characteristics and data imprecision simultaneously. This combined and novel approach produces ideal location recommendations with a comprehensive and highly reliable scientific methodology.

2. RESEARCH METHOD

2.1 Research Design

This research adopts the classification of Applied Research with a Quantitative approach, which specifically focuses on the Development of Hybrid Models within the framework of Multi-Criteria Decision Making (MCDM). The main objective of this design is to design, modify, and validate an innovative mathematical model. Integration of Modified Min-Max Fuzzy TOPSIS with Entropy Weighting. This design is very relevant because the issue of strategic location selection, which involves ambiguous and conflicting criteria, requires a rational, computationally based ranking solution that is able to handle data uncertainty. The case study used is located in Batubara Regency, North Sumatra, with five alternative locations (Madang Deras, Air Putih, Datuk LP, Sei Balai, and LP Pesisir) evaluated based on six criteria (Number of schools, Number of students, Rice production, Road condition, Average travel time and Average distance to the location). The data used are secondary data that have been converted and represented in Triangular Fuzzy Numbers (TFN) to accommodate the assessment uncertainty.

This study combines two key concepts: fuzzy logic and multicriteria decision-making (MCDM), the representation of which will be explained in the following section.

$$\mathbf{D} = \begin{array}{c|cccc} & \mathrm{Crt}_1 & \mathrm{Crt}_2 & \cdots & \mathrm{Crt}_n \\ \hline \mathrm{Alt}_1 & a_{11} & a_{12} & \cdots & a_{1n} \\ \mathrm{Alt}_2 & a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathrm{Alt}_m & a_{m1} & a_{m2} & \cdots & a_{mn} \end{array}$$

Suppose $W = [w_1, w_2, \ldots, w_n]$ is a vector of weights for each criterion, provided that the total weights are equal to 1, that is $\sum_{j=1}^{n} w_j = 1$. Each criterion Crt_j ($j = 1$ up to n) is assessed against the alternative locations (for $i = 1$ up to m). The value is an element of the Decision matrix that indicates the assessment of the i alternative against the j criterion. This matrix is the basis for the calculation process to determine the most appropriate location.

2.2 Literature Review and Problem Identification

Multi-Criteria Decision Making (MCDM) or MCDA is an important area of management science that focuses on selecting the best alternative from a set of options. This process fundamentally involves resolving conflicts and competing outcomes among multiple criteria simultaneously, providing logical and documented support for decision-makers [15]. MCDM acts as a quantitative tool to formulate complex problems, including qualitative and quantitative data, into an organized mathematical model [16], ensuring that decisions take into account multiple factors such as accessibility and infrastructure. Broadly speaking, MCDM is divided into Multi-Objective Decision Making (MODM) for optimization problems, and Multi-Attribute Decision Making (MADM) for determining, ranking, or prioritizing existing alternatives [17]. Every MCDM problem, especially MADM, has three main components: Alternatives (choice options), Criteria (assessment elements that form a matrix), and Weights (the importance of criteria, which can be determined objectively or subjectively) [2]. These criteria are then classified into Profit Criteria (higher values are better) and Cost Criteria (lower values are better) for the normalization process.

Criteria weighting is a fundamental step in MCDM, determining the priority level of criteria and significantly influencing the quality of the final decision [18]. Weighting methods are classified into three categories based on their information sources: Subjective Methods (such as AHP), which rely on expert judgment and are useful for qualitative criteria; Objective Methods (such as the Entropy Method), which use mathematical calculations from matrix data to ensure unbiased weighting; and Hybrid Methods, which combine subjective and objective strengths to achieve balance [19]. The Entropy Method was specifically chosen because it offers total objectivity by determining weights based solely on the structure and distribution of the data, which are significant signs of validity [19]. This information theory-based method serves as an indicator of the level of uncertainty or variation in the data, effectively measuring the discriminatory ability of criteria, where criteria with low variation (high entropy) will result in lower weights due to their less importance in the ranking [18]. With fully mathematical calculations, Entropy guarantees the consistency and reproducibility of weights, ensuring that criteria with high discrimination ability will have the greatest influence on the final decision outcome.

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), developed by Hwang and Yoon (1981), is an MCDM method that selects alternatives based on the shortest distance to the positive ideal solution and the longest distance from the negative ideal solution [20]. TOPSIS is efficient in generating rational rankings and is effective for problems involving multiple criteria because it considers both ideal and anti-ideal solutions simultaneously. Fuzzy TOPSIS (FTOPSIS) is the most frequently used development because it integrates Fuzzy Logic, which is important for supporting decision-making based on inaccurate or unclear data [21] [22]. In FTOPSIS, the performance assessment and criteria weights are expressed as Triangular Fuzzy Numbers (TFN), and the steps include determining linguistic weights/assessments, matrix normalization, determining FPIS (Fuzzy Positive Ideal Solution) and FNIS (Fuzzy Negative Ideal Solution), measuring distances, and calculating the Proximity Coefficient for ranking [23][24][22]. The next variant, Min-Max Fuzzy TOPSIS, is an improvement that utilizes the min–max operation in the solution procedure to handle higher uncertainties, resulting in more robust and flexible solutions [17] [25]. The Min-Max procedure involves normalization based on cost/benefit criteria, determination of extreme solutions, calculation of weighted strength (closeness to negative solutions) and weakness (closeness to positive solutions) indices, and finally the use of the min–max distance ratio to determine the highest alternative performance score as the best choice [2].

This literature review highlights important studies integrating the TOPSIS ranking method and its variations, such as Fuzzy TOPSIS (FTOPSIS), with objective weighting techniques such as the Entropy Method and its variations, particularly in the context of location-determination or related optimization problems, where most studies have used TOPSIS or FTOPSIS as efficient ranking methods. Methodologically, a highly related study is the study by [26], who developed a new Fuzzy Entropy measure and integrated it with Fuzzy TOPSIS for COVID-19 risk assessment, proving the validity of this hybrid architecture. The incorporation of MCDM methods to achieve objectivity is also supported by [27], who applied a hybrid Entropy-TOPSIS approach to rank electric vehicle (EV) options by objectively assigning criteria weights using the Entropy Method. The importance of weight objectivity in the context of high uncertainty is also validated by [28], who combined Weighted Cross-Entropy with TOPSIS for personnel selection, emphasizing the need for Entropy-based weights. The most structurally similar study is that of [29], who proposed a hybrid Entropy-Fuzzy TOPSIS model for financial performance analysis with objective criteria weighting, although lacking the implementation of Min-Max operations. The use of the hybrid Entropy-TOPSIS method for objective location problems is seen in the study of [30] in urban vitality evaluation (ETM Model), and for financial risk analysis by [31], although both used conventional TOPSIS. [32] further supports this main methodological combination, namely the integration of the New Entropy Measure of Fuzzy Sets with Fuzzy TOPSIS (F-TOPSIS) in the context of location selection (tourist destinations). The principles of objectivity and uncertainty handling are re-examined by [33], who integrated Fuzzy TOPSIS with Entropy for natural gas analysis, although still using conventional Fuzzy TOPSIS. Other studies demonstrate the application of MCDM methods in industrial optimization, such as the use of AHP in a truck flow study by [20], which demonstrated the efficiency of a hybrid strategy. The most methodologically and contextually similar study is [2], which applied Min-Max Fuzzy TOPSIS for campus siting, providing strong validation for the proposed framework, although it did not integrate Entropy Weighting. The importance of a hybrid approach in project location optimization is also emphasized by [34], who combined Modified Composite TOPSIS with AHP. Efforts to improve the consistency of conventional TOPSIS are reflected in the study of [35] through the development of a Modified Ranking Index. Meanwhile, a comparative study of AHP and TOPSIS for MSME site selection in Indonesia by [25] confirmed the validity of TOPSIS in a location context, despite using subjective weighting, and a comparative analysis of CoCoSo and EDAS with Entropy weighting for EVCS siting by [3] demonstrated the need for Fuzzy environment integration to address data uncertainty. Therefore, this research proposes a novel, hybrid framework that seamlessly integrates Entropy Weighting and Min-Max Fuzzy TOPSIS to deliver an objective, highly robust, and consistent model, directly addressing the existing methodological limitations and providing a superior tool for decision-makers in complex strategic siting problems.

2.3 Analytical Methods and Validation

The analysis process is carried out by applying the Entropy-Weighted Min-Max Fuzzy TOPSIS framework to obtain objective and consistent alternative rankings.

Algorithm:

Step 1. Determine the Objective and Decision Criteria. Identify the main objective of the decision-making process. Classify each criterion as either a cost or a benefit criterion.

Step 2. Data Collection. Collect crisp data for all alternatives X_i. Convert crisp data into Triangular Fuzzy Numbers (TFN) $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$.

Step 3. Determine Criteria Weights Using the Entropy Method. This stage produces objective weights w_j to be used in the next step.

a. Normalization of Probability Data : Convert crisp data to normalized probability values (p_{ij}):

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{1}$$

Where x_{ij} is the crisp value (or mean of TFN) of alternative X_i on criterion C_j, and the denominator represents the total of each criterion across all alternatives $\sum_{i=1}^{m} x_{ij}$.

b. Entropy Calculation (e_j) :

$$e_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} p_{ij} \ln(p_{ij}) \tag{2}$$

where m is the total number of alternatives.

c. Degree of Divergence (d_j) :

$$d_j = 1 - e_j \tag{3}$$

d. Calculation of Criteria Weights (w_j) : The final weight of the criteria (w_j) is obtained by normalizing the divergence value.

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{4}$$

where n is the total number of criteria.

Step 4. Implementation of Min–Max Fuzzy TOPSIS

a. Fuzzy Normalization :
For cost criteria :

$$Cost : \tilde{x}'_{ij} = (\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}) \text{ with } l_j^- = \min_i \{l_{ij}\} \tag{5}$$

For benefit criteria:

$$Benefit : \tilde{x}'_{ij} = (\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{u_j^+}, \frac{u_{ij}}{u_j^+}) \text{ with } u_j^+ = \max_i \{u_{ij}\} \tag{6}$$

b. Determine Extreme Solutions :

$$\text{Negative Ideal Solution (NIS) : } \tilde{x}_j^- = \min_i \{\tilde{x}_{ij}\} \tag{7}$$

$$\text{Positive Ideal Solution (PIS) : } \tilde{x}_j^+ = \max_i \{\tilde{x}_{ij}\} \tag{8}$$

c. Distance Measurement :
Calculate the Euclidean distance $D(\tilde{A}, \tilde{B})$ between two TFNs $\tilde{A} = (l_A, m_A, u_A)$ and $\tilde{B} = (l_B, m_B, u_B)$

$$D(\tilde{A}, \tilde{B}) = \sqrt{\frac{1}{3}[(l_A - l_B)^2 + (m_A - m_B)^2 + (u_A - u_B)^2]} \tag{9}$$

d. Strength (S_{ij}) : Distance to negative solution $\tilde{x}_j^-$:

$$S_{ij} = D(\tilde{x}_{ij}, \tilde{x}_j^-) \tag{10}$$

e. Weakness (W_{ij}) : Distance to positive solution $\tilde{x}_j^+$:

$$W_{ij} = D(\tilde{x}_{ij}, \tilde{x}_j^+) \tag{11}$$

Step 5. Integration of Entropy Weights into Fuzzy TOPSIS. Use the entropy weights w_j (from Step 3) as weighting factors.

a. Exterior Product of Fuzzy Numbers ($\otimes$) : If the weight wt_j is a crisp number λ and the distance D is TFN (l_D, m_D, u_D), then:

$$\lambda \otimes D = (\lambda \cdot l_D, \lambda \cdot m_D, \lambda \cdot u_D) \tag{12}$$

b. Weighted Strength Index (W_i^-) :

$$W_i^- = \sum_{j=1}^{n} wt_j \otimes D(\tilde{x}_{ij}, \tilde{x}_j^-) = (d_{iL}^-, d_{iM}^-, d_{iU}^-) \tag{13}$$

c. Weighted Weakness Index (W_i^+) :

$$W_i^+ = \sum_{j=1}^{n} wt_j \otimes D(\tilde{x}_{ij}, \tilde{x}_j^+) = (d_{iL}^+, d_{iM}^+, d_{iU}^+) \tag{14}$$

Step 6. Evaluation and Ranking of Alternatives

a. Global Indices (Min–Max):

$$\text{Strength: : } NgW^- = \min_i \{W_i^-\} \text{ and } NgW^+ = \max_i \{W_i^-\} \tag{15}$$

$$\text{Weakness: : } PsW^- = \min_i \{W_i^+\} \text{ and } PsW^+ = \max_i \{W_i^+\} \tag{16}$$

b. Negative and Positive Indices:

Negative index: (Alt_i^-)

$$Alt_i^- = \frac{D(W_i^-, NgW^+)}{D(W_i^-, NgW^+) + D(W_i^-, NgW^-)} \tag{17}$$

Positive index (Alt_i^+)

$$Alt_i^+ = \frac{D(W_i^+, PsW^+)}{D(W_i^+, PsW^+) + D(W_i^+, PsW^-)} \tag{18}$$

c. Performance Index (Alt_i^*) :

$$Alt_i^* = Alt_i^+ \cdot (1 - Alt_i^-) \tag{19}$$

d. Ranking: Arrange the alternatives by value Alt_i^*. The highest value is the best.

Step 7. Proposed Model Verification: Perform sensitivity analysis by comparing the results using varying criteria weighting methods with equal weights.

Step 8. Results and Analysis Interpret the ranking results (Alt_i^*).

By applying the method of related performance index for alternatives, we need to determine the ranked sequence of the best alternatives.

2.4 Software and Tools

All mathematical calculations, including the Triangular Fuzzy Number operation, Entropy calculation, and the Min-Max Fuzzy TOPSIS algorithm, are performed computationally. The specifics of the Python software used are not listed in this text, but the analysis process follows the steps of the mathematical algorithm described in detail.

3. RESULT AND ANALYSIS

The results of this study are presented in two main parts: the determination of objective weights for the evaluation criteria using the Entropy Method and the final ranking of strategic locations using the Modified Min-Max Fuzzy TOPSIS algorithm. The analysis compares the results derived from the objective weighting with a conventional uniform weighting approach to validate the model's robustness and objectivity.

3.1 Objective Weighting of Criteria via Entropy Method

The initial step in the hybrid framework was to calculate the objective weights (w_j) for the six evaluation criteria Crt_1 to Crt_6 using the Entropy method. The Entropy method assigns higher weights to criteria exhibiting greater disparity or discriminatory power across the five alternatives, thereby reducing the influence of subjective expert bias. The calculation of these weights, corresponding to Step 3 in the algorithm, by using Eqs. (1), (2), (3), and (4) in Step 3 resulted in the values summarized in Table 3.

Table 1. Objective Weights of Criteria Determined by the Entropy Method (W_j)

Criteria	$\sum p_{ij}$	$\sum p_{ij}\ln(p_{ij})$	E_j	d_j	w_j^{Ent}
Crt_1	3.518	-1.559	0.968	0.032	0.264
Crt_2	3.575	-1.553	0.965	0.035	0.294
Crt_3	3.336	-1.560	0.969	0.031	0.256
Crt_4	3.944	-1.592	0.989	0.011	0.093
Crt_5	4.072	-1.598	0.993	0.007	0.060
Crt_6	3.965	-1.603	0.996	0.004	0.034
Total	22.410	-9.464	5.880	0.120	1.000

The analysis of Table 3 shows that the criterion Number of Students, Crt_2 with $w_2^{Ent} = 0.294$ obtained the highest weight. This finding indicates that the variation in the number of students across the five potential locations was the most significant factor, granting it the highest discriminatory power in the decision-making process. The distribution of weights confirms the suitability of the Entropy method in providing a rational and objective allocation of criterion importance based on the intrinsic data structure, mitigating potential subjective biases.

3.2 Result analysis

The algorithm discussed is a multicriteria decision-making approach that combines the Entropy Method to determine objective weights and Min-Max Fuzzy TOPSIS for ranking. This process begins by collecting data, converting it into Triangular Fuzzy Numbers (TFN), and then using the Entropy Method (Step 3) to generate criterion weights w_j. These weights are calculated through probability normalization (P_{ij}) via Eqs (1), Entropy calculation (e_j) with Eqs (2), and divergence (d_j) according to Eqs (3), the result of which, w_j^{En}, is presented in Table 3.

Next, the implementation of Min-Max Fuzzy TOPSIS begins with Fuzzy Normalization and determination of extreme solutions: Negative Ideal Solution $(NIS, \tilde{x}_j^-)$ and Positive Ideal Solution $(PIS, \tilde{x}_j^+)$. The results of normalization and extreme solutions are presented in Table 4. By using the Euclidean Distance $(D(\tilde{A}, \tilde{B}))$ in Eqs (9), the Strength Matrix (S_{ij}) to NIS and the Weakness Matrix (W_{ij}) to PIS in Eqs (10), (11) are calculated, and the results are in Table 5 and Table 6, respectively.

Finally, the Entropy weights are integrated to produce the Weighted Strength Index (W_i^-) and Weighted Weakness Index (W_i^+) in Eqs (13),(14), respectively, the results of which are presented in Table 7, and the Global Indices in Table 8. The final step (Step 6) is the calculation of the Negative Index (Alt_i^-), Positive Index (Alt_i^+), and Performance Index (Alt_i^*), which are used for ranking. These final values, along with the rankings of the alternatives, are presented in Table 9.

Table 2. Normalized matrix and the extreme solutions

Normalized Matrix and The Extreme Solutions			
$Alt./Crt.$	Crt_1	Crt_2	Crt_3
Alt_1	(0.894, 0.906, 0.918)	(0.981, 0.981, 0.982)	(0.832, 0.832, 0.832)
Alt_2	(0.976, 0.988, 1.000)	(1.000, 1.000, 1.000)	(1.000, 1.000, 1.000)
Alt_3	(0.365, 0.376, 0.388)	(0.396, 0.396, 0.396)	(0.445, 0.445, 0.445)
Alt_4	(0.624, 0.635, 0.647)	(0.558, 0.558, 0.558)	(0.556, 0.556, 0.556)
Alt_5	(0.600, 0.612, 0.624)	(0.639, 0.639, 0.640)	(0.502, 0.502, 0.502)
Alt^-	(0.365, 0.376, 0.388)	(0.396, 0.396, 0.396)	(0.445, 0.445, 0.445)
Alt^+	(0.976, 0.988, 1.000)	(1.000, 1.000, 1.000)	(1.000, 1.000, 1.000)
$Alt./Crt.$	Crt_4	Crt_5	Crt_6
Alt_1	(0.556, 0.583, 0.611)	(0.597, 0.604, 0.611)	(0.678, 0.696, 0.715)
Alt_2	(0.667, 0.694, 0.722)	(0.795, 0.807, 0.820)	(0.728, 0.748, 0.770)
Alt_3	(0.722, 0.750, 0.778)	(0.963, 0.981, 1.000)	(0.929, 0.963, 1.000)

Alt_4	(0.917, 0.944, 0.972)	(0.807, 0.820, 0.833)	(0.734, 0.755, 0.777)
Alt_5	(0.944, 0.972, 1.000)	(0.846, 0.860, 0.874)	(0.779, 0.803, 0.828)
Alt^-	(0.556, 0.583, 0.611)	(0.597, 0.604, 0.611)	(0.678, 0.696, 0.715)
Alt^+	(0.944, 0.972, 1.000)	(0.963, 0.981, 1.000)	(0.929, 0.963, 1.000)

Table 3. Assessment of Competitiveness Using a Strength Matrix

Assessment of Competitiveness Using a Strength Matrix						
$Alt./Crt.$	Crt_1	Crt_2	Crt_3	Crt_4	Crt_5	Crt_6
Alt_1	0.529	0.585	0.387	0.000	0.000	0.000
Alt_2	0.612	0.604	0.555	0.111	0.203	0.053
Alt_3	0.000	0.000	0.000	0.167	0.377	0.268
Alt_4	0.259	0.161	0.111	0.361	0.216	0.059
Alt_5	0.235	0.243	0.057	0.389	0.256	0.108

Table 4. Assessment of Competitiveness Through a Weakness Matrix

Assessment of Competitiveness Through a Weakness Matrix						
$Alt./Crt.$	Crt_1	Crt_2	Crt_3	Crt_4	Crt_5	Crt_6
Alt_1	0.082	0.018	0.168	0.389	0.000	0.268
Alt_2	0.000	0.000	0.000	0.278	0.203	0.216
Alt_3	0.612	0.604	0.555	0.222	0.377	0.000
Alt_4	0.353	0.442	0.444	0.028	0.216	0.209
Alt_5	0.376	0.360	0.498	0.000	0.256	0.161

Table 5. The Indices with Weights

The Indices with Weights		
$Alt./Crt.$	W_i^-	W_i^+
Alt_1	(0.336, 0.411, 0.486)	(0.069, 0.115, 0.161)
Alt_2	(0.398, 0.505, 0.612)	(0.010, 0.045, 0.080)
Alt_3	(0.007, 0.047, 0.088)	(0.406, 0.524, 0.643)
Alt_4	(0.134, 0.193, 0.251)	(0.275, 0.359, 0.444)
Alt_5	(0.139, 0.203, 0.267)	(0.271, 0.354, 0.436)

Table 6. The strength and weakness index solutions with significant weight.

The Strength And Weakness Index Solutions with Significant Weight			
NgW^-	NgW^+	PsW^-	PsW^+
(0.007, 0.047, 0.088)	(0.398, 0.505, 0.612)	(0.010, 0.045, 0.080)	(0.406, 0.524, 0.643)

Table 7. The indices of positive, negative, and closeness coefficients.

The Indices of Positive, Negative, and Closeness Coefficients				
$Alt.$	Alt_i^-	Alt_i^+	Alt_i^*	$Rank$
Alt_1	0.212	0.854	0.673	1
Alt_2	0.000	0.531	0.531	2
Alt_3	1.000	0.000	0.000	5

Alt_4	0.683	0.439	0.139	4
Alt_5	0.659	0.445	0.152	3

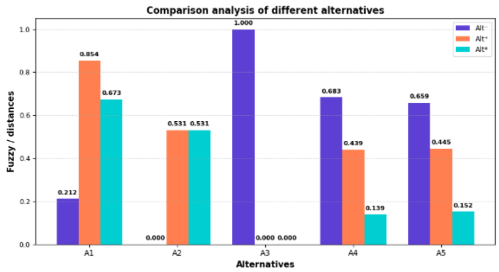

Figure 1. Histography of indices for negativity, positivity, and closeness coefficients

From the above table, we concluded that the ranking order of overall performance indices is $\text{Alt}_1 > \text{Alt}_2 > \text{Alt}_5 > \text{Alt}_4 > \text{Alt}_3$. The graphical presentation of these values is given in the Fig.1. Out of these, we concluded that the $Alt_1^* = 0.673$ has the largest value and $Alt_3^* = 0.000$ has the smallest value.

Table 8. Performance Index Values Comparison Across Weighting Methods

Comparative Results of the Original, Proposed, and Uniform Weighting Methods			
$Alt.$	Original	Proposed	Uniform
Alt_1	0.588	0.673	0.449
Alt_2	0.519	0.531	0.521
Alt_3	0.000	0.000	0.000
Alt_4	0.194	0.139	0.128
Alt_5	0.497	0.152	0.174

Table 8 shows a comparison of performance index values among three weighting techniques Original, Proposed, and Uniform for five options. The findings indicate that the Proposed method typically yields better performance ratings for stronger alternatives, especially Alt_1 and Alt_2, suggesting that this weighting strategy highlights criteria where these options excel. Alt_1 shows the greatest enhancement, rising from 0.588 with the Original method to 0.673 using the Proposed method, while the Uniform method delivers a lesser value of 0.449. Alt_2 shows a consistent level of stability across all approaches, indicating reliable performance irrespective of the weighting used. Alt_3 scores 0 in every scenario, indicating its consistently underwhelming performance. Conversely, Alt_4 and Alt_5 show considerable reductions when using the Proposed and Uniform methods in comparison to the Original, suggesting that their positive performance with the original method is influenced by the initial weight configuration. The comparison shows that the Proposed method improves differentiation between alternatives by emphasizing top-performing choices and lowering the scores of less capable ones.

4. CONCLUSION

This study successfully developed an enhanced multi-criteria decision-making (MCDM) framework by integrating the Entropy Method with the Modified Min–Max Fuzzy TOPSIS to strengthen decision accuracy under uncertainty. Numerical validation shows that the proposed method provides a significant improvement over existing approaches. When compared with the original Min–Max Fuzzy TOPSIS, the Performance Index of the best alternative, Madang Deras (Alt_1), increased from 0.588 to 0.673, representing a 14.46% improvement in ranking accuracy. Furthermore, when evaluated against a model using uniform weighting, the Performance Index increased from 0.449 to 0.673, reflecting a substantial 49.89% enhancement. These results demonstrate that entropy-based objective weighting meaningfully improves the discriminative power of the decision model and reduces the bias introduced by equal or subjective weights. Overall, the proposed hybrid framework offers a more stable, accurate, and comprehensive approach for strategic location selection, effectively addressing conflicting criteria and uncertainty within the Batubara Regency case study.

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