






## Balancing Sustainability and Decision Maker Preferences in Regional Development Location Selection: A Multi-criteria Approach Using AHP and Fuzzy Goal Programming

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<https://doi.org/10.18280/mmep.110710>

### ABSTRACT

**Received:** 12 April 2024

**Revised:** 3 July 2024

**Accepted:** 15 July 2024

**Available online:** 31 July 2024

#### Keywords:

*Fuzzy Goal Programming, Analytical Hierarchy Process, decision maker preferences, multi criteria selection, palm oil industry*

In this study, we address the challenge of balancing sustainability and decision-maker preferences in regional development location selections. We propose a multi-criteria decision-making framework combining the Analytical Hierarchy Process (AHP) and Fuzzy Goal Programming (FGP) to evaluate potential sites. AHP is utilized to prioritize criteria, incorporating both quantitative and qualitative factors, while FGP allows for the accommodation of uncertainty and conflicting goals. Our findings reveal that this integrated approach provides a robust, systematic method for identifying optimal locations that align with both sustainability goals and stakeholder priorities. The analysis revealed the following satisfaction levels: Price 61.11%, Quality 80.4%, Delivery Time 79.3%, Carbon Emission 91.76%, and Preference 51.18%. The findings emphasize the complex process of selecting vendors within the palm oil supply chain. The implications of this research suggest enhanced decision-making efficiency and effectiveness in regional planning, promoting sustainable development practices.

## 1. INTRODUCTION

In the current period of regional development, there is a strong need for sustainable growth, which has resulted in a growing focus on incorporating sustainability factors into decision-making processes. Although there has been a tremendous increase in research and methodology focused on improving the selection of locations for regional development, there are still notable gaps and limitations in present approaches. Conventional approaches frequently struggle to effectively reconcile the complex and different aspects of sustainability, which include environmental, social, and economic components, with the specific preferences and goals of various stakeholders. Furthermore, these approaches often do not possess the adaptability to handle the inherent uncertainties and ambiguities in decision-making situations, especially those that involve subjective assessments and qualitative standards [1-4]. The conventional Analytical Hierarchy Process (AHP) is commonly employed for its systematic approach to multi-criteria decision-making. It is particularly effective in prioritizing criteria and combining expert viewpoints. However, it has limitations when it comes to dealing with vagueness and lack of precision in human judgments [5, 6]. However, Goal Programming (GP) is not as successful in handling the qualitative parts of decision criteria and the subjective character of stakeholder preferences, despite its effectiveness in managing many, frequently conflicting objectives. In addition, current models often fail to consider the dynamic and linked characteristics of

sustainability issues, resulting in less than ideal and perhaps unsustainable development results. This study aims to fill these existing gaps by introducing a comprehensive multi-criteria decision-making framework that integrates the advantages of Analytic Hierarchy Process (AHP) and Fuzzy Goal Programming (FGP) [7-9]. The AHP component of our methodology allows for the methodical assessment and ranking of a complete range of criteria, including both quantitative and qualitative elements, so assuring a fair and thorough analysis of all pertinent aspects of sustainability. Our technique incorporates FGP to effectively address the ambiguities and imprecision that are inherent in the decision-making process [10, 11]. FGP's ability to integrate fuzzy logic enables the accurate modeling of stakeholder preferences and goals, capturing the intricate and subjective character of these preferences in the actual world. This integration not only improves the adaptability and strength of the decision-making process but also guarantees that the chosen locations are more closely aligned with both sustainability goals and stakeholder preferences. In addition, our research presents a new use of this integrated strategy in the field of regional development. We provide a comprehensive case study that showcases its practical usefulness and efficiency [12, 13]. The results of our case study demonstrate that the suggested framework greatly enhances the quality and long-term viability of judgments about location selection. It provides a more thorough and nuanced comprehension of the compromises that are inherent in such selections. This work enhances the current knowledge by addressing a significant gap in the literature and offering a

useful tool for decision-makers in regional planning. The findings of our research have broader ramifications beyond the specific field of regional development [14-18]. They provide valuable insights and approaches that may be applied to other areas where making decisions based on several criteria is essential. Our work facilitates the incorporation of sustainability into decision-making processes, thereby promoting well-informed, equitable, and environmentally responsible development practices [19]. To summarize, this study emphasizes the significance of creating advanced decision-making instruments that can tackle the intricate and interconnected obstacles of sustainability and stakeholder preferences. The integration of the Analytic Hierarchy Process (AHP) and the Fuzzy Goal Programming (FGP) framework is a significant advancement in addressing a critical problem in current regional development. This framework provides a strong, adaptable, and realistic solution [20].

The process of choosing the most suitable sites for regional development initiatives entails the careful consideration and weighing of different, frequently contradictory, factors. Multi-criteria decision-making (MCDM) methodologies, such as the Analytical Hierarchy Process (AHP) and Fuzzy Goal Programming (FGP), are useful methods for evaluating potential sites in this situation. The main factors considered in this assessment are Price, Quality, Delivery Time, Carbon Emission, and Preference. The AHP technique initiates by organizing these criteria into a hierarchical model, with the primary objective (best location selection) at the highest level, followed by several degrees of criterion and sub-criteria [21-23]. Decision-makers utilize pairwise comparisons to evaluate the relative significance of each criterion, thereby converting subjective judgments into measurable weights. The weights assigned to each criterion allow for a thorough assessment of potential locations, indicating their relative importance. When comparing Price and Quality, decision-makers assess the relative significance of cost vs the level of services or products provided. Similarly, an analysis is conducted to compare the Delivery Time and Carbon Emission, assessing the balance between timeliness and ecological consequences. The Preference criterion considers the subjective preferences of stakeholders, ensuring that the selected location is in line with their specific needs and objectives [24, 25].

After determining the criteria weights, the subsequent step is to utilize Fuzzy Goal Programming to handle the inherent ambiguities and vagueness in human judgments. FGP enhances classical Goal Programming by integrating fuzzy logic, enabling the representation of imprecise and ambiguous data. This is especially advantageous in practical situations when precise data may be lacking or where preferences are not rigidly limited to two options. Within the FGP framework, every objective (related to Price, Quality, Delivery Time, Carbon Emission, and Preference) is expressed using fuzzy phrases, indicating acceptable ranges and levels of satisfaction instead of specific targets. Instead of imposing a rigid cost limit, the Price objective could be defined as a fuzzy set, where lower prices are favored but slightly higher costs are permissible within a specific range. Similarly, the Quality criterion could be represented to encompass diverse levels of satisfaction with many quality standards, rather than a singular acceptable norm [26, 27]. This adaptability enables the decision-making process to more accurately capture the intricacies of real-life situations [28].

The process of integrating AHP and FGP starts with normalizing the criteria weights derived from AHP. These

normalized weights are then utilized to develop the FGP model. The FGP model utilizes these weights as coefficients in the objective function, which symbolize the level of accomplishment for each fuzzy goal [29]. The main goal is to maximize the total level of goal accomplishment, while adhering to the limitations set by the fuzzy goals. In this concept, the requirements are not regarded as inflexible limits but rather as adaptable objectives that can be partially fulfilled to different degrees. When analyzing potential locations, each site is examined based on the fuzzy criteria of Price, Quality, Delivery Time, Carbon Emission, and Preference. The website that has the highest overall level of goal satisfaction is considered the most optimal choice. This approach guarantees that the chosen location achieves the optimal equilibrium among the conflicting requirements, taking into account both quantitative and qualitative considerations [30-32].

For example, let's suppose a situation where three possible locations are being assessed. Every location is evaluated based on the following criteria: Price (development cost), Quality (infrastructure and service standards), Delivery Time (time needed to make the location functional), Carbon Emission (environmental impact of development and operations), and Preference (conformity with stakeholder objectives). The Analytic Hierarchy Process (AHP) is utilized to determine the respective weights of these criteria through pairwise comparisons [33]. This process yields weights of 0.25 for Price, 0.20 for Quality, 0.15 for Delivery Time, 0.30 for Carbon Emission, and 0.10 for Preference. The weights provided represent the level of importance assigned to each criterion by the decision-makers. Subsequently, the FGP model is constructed utilizing the specified weights and the fuzzy goals assigned to each criterion [34]. For example, the Price aim can be described as a fuzzy set with a membership function that gradually diminishes as expenses rise, indicating a preference for lower prices but still allowing for greater costs within an acceptable range. Similarly, the Quality aim could be represented by a membership function that exhibits an upward trend as the standards of infrastructure and services improve, but with diminishing marginal rewards at the greatest levels of quality. The delivery time can be represented to account for the urgency of establishing the location, prioritizing shorter durations while allowing for some flexibility for longer periods. The carbon emission targets prioritize fewer emissions, employing a membership function that diminishes as emissions rise, indicating a significant inclination towards ecologically sound choices. Preference criteria would encompass stakeholder-specific requirements, such as the proximity to important markets or the alignment with corporate goals, using a membership function customized to meet these specific demands.

Subsequently, every possible location is assessed based on these ambiguous objectives, leading to a collection of satisfaction levels for each criterion. The FGP model combines these satisfaction levels to determine the overall level of goal attainment for each location. The best site is determined by selecting the place with the highest overall satisfaction level. This ensures a well-rounded solution that takes into consideration the various aspects of sustainability and the preferences of stakeholders.

The utilization of both Analytic Hierarchy Process (AHP) and Fuzzy Goal Programming (FGP) in the process of selecting a location for regional development has numerous benefits. It facilitates a methodical and organized assessment of various criteria, guaranteeing the inclusion of all pertinent

aspects. Utilizing fuzzy logic in FGP improves the adaptability and resilience of the decision-making procedure, tolerating uncertainties and imprecisions in data and preferences. This approach also guarantees that the chosen site is in line with both sustainability targets and stakeholder interests, fostering equitable and sustainable regional growth. This technique combines both quantitative and qualitative assessments to create a comprehensive framework for making well-informed and balanced judgments in complicated and unpredictable situations. The utilization of both Analytic Hierarchy Process (AHP) and Fuzzy Goal Programming (FGP) offers a potent method for optimizing the selection of locations in regional growth. This strategy ensures that the selected location achieves the optimal overall balance among conflicting objectives by systematically prioritizing criteria and taking into account uncertainties and stakeholder preferences. It promotes sustainable and informed decision-making.

## 2. METHODS

The supplier selection and evaluation process are very flexible, it depends on the situation and industry, so there is no single way. However, there are several methods that can be used in supplier selection and evaluation, each method has its own advantages depending on the needs of the company [35]. Some of these studies use heuristic methods: using Genetic Algorithm with the objective function of price and reliability, reliability is related to the supplier's ability to meet the company's needs precisely, using two heuristic methods namely Particle Swarm Optimization (PSO) and Differential Equation (DE) to determine the best supplier and order allocation with the objective function of minimizing fixed costs and purchasing costs, storage and transportation costs. used the best-worst method to determine the weight of the criteria, while a combination of Genetic Algorithm and AHP methods was used to determine the best order and supplier.

Some researches use a combination of MCDM and MILP select suppliers in a composite company using the Best Worst Method for weighting criteria and using MILP with the objective function of maximizing supplier weights for order allocation. Islam et al. [36] weighted the suppliers by integrating DEA with AHP and TOPSIS and used MILP with the objective function of minimizing the emergency order price for order allocation used AHP method for supplier weights and combined Weighted Sum method and  $\epsilon$ -constraint method to determine order allocation with six objective functions of cost, economic value, environment, social, risk and inflation [37-39].

Unfortunately, previous studies were deterministic and did not consider uncertainty. Some studies that accommodate uncertainty are as follows: conducted supplier selection using weighted Fuzzy Goal Programming with the objective function of minimizing price, quality and delivery time using the objective functions of price, delivery delay, quality of goods and carbon emissions on rice, wheat, and rye suppliers, this study uses machine learning to forecast the needs of food companies, the model that used is a SMILP stochastic model uses Weighted Additive Function to transform a multi objective function into a single objective with Fuzzy parameters which is further solved by the Resolution Method. Gidiagba et al. [40] Using Fuzzy AHP and Interval TOPSIS methods to determine supplier weighting and Simulation-Optimization to determine order allocation with the objective

function of maximizing supplier ranking and minimizing price. Rahman et al. [41] used the Fuzzy ANP method to select the best criteria and sub-criteria, then the Fuzzy Decision-Making Trial and Evaluation (DEMATEL) method was used to see the relationship between the main criteria, then TOPSIS was used to weight suppliers. There are three objective functions used, which is minimizing the cost, maximizing the weight of the supplier and maximizing the reliability of the supply chain. Combined fuzzy sets with PROMETHEE II by considering three criteria, which are the basic, ordering, and sustainable criteria in Petrochemical Companies. The integration of Fuzzy AHP with three MCDM methods, namely MABAC (Multi Attribute Border Approximation Area Comparison), WASPAS (Weighted Aggregated Sum-Product Assessment) and TOPSIS (Technique for order preference by similarity to ideal solution) to determine the best supplier in the automotive industry where there are 6 environmental criteria and three conventional criteria namely price, quality and service. uses gray numbers in the DEMATEL method to determine the weight of criteria and the Gray Simple Additive Weighting Technique (GSAW) method to decide the weight of suppliers. This research uses Fuzzy Goal Programming because it can accommodate more than one objective function and there is uncertainty in the form of using fuzzy numbers, Chai et al. [42] using Fuzzy Goal Programming in the selection and allocation of shares in portfolios on the Indian stock exchange. Meanwhile, related to the problem of selecting FFB suppliers, Ho et al. [43] conducted the selection and allocation of FFB suppliers with the objective functions of operational costs, transportation costs, CPO production costs, and process costs and palm oil waste, the model was solved using the Generalized Reduced Gradient Method, selected palm oil suppliers with criteria such as quality, delivery, price, service etc. using the PROMETHEE supplier weighting method [44, 45]. We will then solve the supplier selection problem that involves environmental consideration, decision-maker preferences, and resource uncertainty in the palm oil industry based on research on the application of fuzzy multicriteria questions.

### 2.1 Mathematical model

Objective Function:

$$\min P = \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T [P_s \cdot Q_{sjt} + O_{sj} \cdot Z_{sjt} + PIV \cdot IV_{jt}] \quad (1)$$

$$\min Q = \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T \left[ \frac{qd_{sj}}{q_{sjt}} \right] \cdot Z_{sjt} \quad (2)$$

$$\min T = \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T \left[ \frac{\lambda}{C_{st}} \cdot Q_{sjt} + \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T \frac{h_{sj}}{Vt} \cdot Z_{sjt} \right] \quad (3)$$

$$\min C = \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T [TE \cdot h_{sj}] \cdot Z_{sjt} + (PE_{jt} \cdot Q_{sjt} + IV_e \cdot IV_{jt}) \quad (4)$$

$$\max S = \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T W_s \cdot Q_{sjt} \quad (5)$$

Subject to:

$$\sum_{s=1}^S Q_{jst} = D_{jt} - I_{V_{jt}}; \quad \forall j, t \quad (6)$$

$$Q_{jst} \leq C_{st} \cdot Z_{sjt}; \quad \forall s, j, t \quad (7)$$

$$\sum_{s=1}^S W_s = 1 \quad (8)$$

$$Q_{jst} \geq 0, \quad Z_{sjt} \in \{0, 1\}; \quad \forall s, j, t \quad (9)$$

Eq. (1) shows that the objective function of minimizing costs is the sum of FFB costs, ordering costs and CPO inventory storage costs. Eq. (2) shows the quality objective function, which is to minimize the rejection of FFB. Eq. (3) shows the time objective function, which is the sum of FFB production time and delivery time. Eq. (4) shows the carbon emission objective function, which is the sum total of carbon emissions for vehicles, FFB processing and CPO inventory storage. Eq. (5) shows the expert's preference for the selected supplier which was determined using AHP. Eq. (6) defines the FFB requirement of POM and CPO inventory by POM, constraint (7) ensures that suppliers do not supply FFB beyond their capacity, Eq. (8) defines supplier weights, constraint (9) is a positive value constraint for order allocation and binary variables.

## 2.2 Analytical Hierarchy Process

The Analytical Hierarchy Process (AHP) is a systematic method for arranging and evaluating intricate decisions using principles from mathematics and psychology. It aids decision-makers in establishing priorities and making optimal judgments by simplifying intricate choices into a sequence of pairwise comparisons, then subsequently combining the outcomes.

### AHP Algorithm in Selection

#### Step 1: Define the Problem and Goal

Goal: Optimal location selection for regional development.

#### Step 2: Structure the Hierarchy

Level 1: Goal

Level 2: Criteria (Price, Quality, Delivery Time, Carbon Emission, Preference)

Level 3: Sub-criteria (if any; in this case, we assume the main criteria are sufficient)

#### Step 3: Construct Pairwise Comparison Matrices

Compare each pair of criteria with respect to their importance towards achieving the goal.

Use a scale of 1 to 9, where 1 indicates equal importance and 9 indicates extreme importance of one criterion over the other.

#### Step 4: Calculate Criteria Weights

Normalize the pairwise comparison matrices.

Compute the eigenvector (priority vector) for each matrix, representing the relative weights of the criteria.

Ensure consistency by calculating the Consistency Ratio (CR). A CR less than 0.1 is generally acceptable.

1. The weight for each row in a column will be summed up ( $s_i$ ).

$$s_i = \sum_{j=1}^n a_{ij}$$

2. Each entry will be normalized, thus normalized entries are obtained  $b_{ij}$ .

$$b_{ij} = \frac{a_{ij}}{s_i}$$

3. The weight for the attribute will be obtained by dividing it by the number of columns.

$$b_{ij} = \frac{1}{m} \left( \sum_{j=1}^m b_{ij} \right)$$

4. Weight of criteria as follow:

$$p_i = \sum_{k=1}^K b_k^{(0)} \cdot b_i^k$$

where,  $p_i$ =Weight criteria;  $b_k^{(0)}$ =Weight provided by pairwise comparison of criteria;  $b_i^k$ =Weight provided by pairwise comparison of alternative considering the criterion.

## 2.3 Fuzzy Goal Programming

Fuzzy Goal Programming (FGP) is an enhanced version of Goal Programming that integrates fuzzy logic to effectively manage the uncertainty and imprecision involved in decision-making.

### Fuzzy Goal Programming Algorithm

#### Step 1: Define Goals and Fuzzy Goals

Goals are defined for each criterion with a desired target value and acceptable range.

Price: Minimize cost

Quality: Maximize quality score

Delivery Time: Minimize time

Carbon Emission: Minimize emissions

Preference: Maximize alignment

#### Step 2: Formulate Fuzzy Membership Functions

Each criterion is represented by a fuzzy membership function to capture the degree of satisfaction.

#### Step 3: Construct the FGP Model

The objective function aims to maximize the overall degree of goal satisfaction, aggregated across all criteria.

Incorporate the criteria weights from AHP into the FGP model.

General Equation for FGP:

$$\max Z = \sum_{i=1}^n w_i \mu_i(x_i)$$

where,  $w_i$  is the weight of the  $i$ -th criterion from AHP,  $\mu_i$  is membership function for the  $i$ -th criterion,  $x_i$  is the decision variable for the  $i$ -th criterion, and  $n$  is the number of criteria.

#### Step 4: Solve the FGP Model

Using linear programming or other suitable optimization techniques, solve the model to find the values of decision variables  $x_i$  that maximize  $Z$ .

This detailed methodology ensures transparency and justifies the selection process by explicitly showing how criteria and sub-criteria are evaluated, weighted, and aggregated to make an informed decision. This approach provides a robust framework for balancing sustainability and stakeholder preferences in location selection for regional development.

a. Establish a fuzzy membership objective function as follows:

$$\theta_k = \begin{cases} 0, & \text{if } F_k \geq F_k^{\alpha\text{-aspire}} \\ \frac{F_k^{\alpha\text{-acc}} - F_k}{F_k^{\alpha\text{-acc}} - F_k^{\alpha\text{-aspire}}}, & \text{if } F_k^{\alpha\text{-aspire}} < F_k < F_k^{\alpha\text{-acc}} \\ 1, & \text{if } F_k \leq F_k^{\alpha\text{-acc}} \end{cases}$$

where,  $F_k^{\alpha\text{-aspire}}$  is lower bound of objective function and  $F_k^{\alpha\text{-acc}}$  is upper bound of objective function.

b. Determine the priority weights for each objective function  $NFW_k$  to transform the multiobjective function to single objective:

$$\max \sum_{k=1}^K NFW_k \cdot \theta_k \quad (10)$$

Subject to:

$$\sum_{k=1}^K NFW_k = 1 \quad \forall k \quad (11)$$

$$\theta_k \leq 1 \quad (12)$$

$$\frac{F_k^{\alpha\text{-acc}} - F_k}{F_k^{\alpha\text{-acc}} - F_k^{\alpha\text{-aspire}}} = \theta_k \quad (13)$$

$$\sum_{S=1}^S I_{fsjt} = D_{fjt}, \quad \forall f; \forall j; \forall t \quad (14)$$

$$I_{fsjt} \leq CS_{fs} \cdot Z_{fsjt}, \quad \forall f; \forall s; \forall j; \forall t \quad (15)$$

$$Z_{fsjt} \in \{0, 1\} \quad \forall f; \forall s; \forall j; \forall t \quad (16)$$

### 3. RESULTS AND DISCUSSION

This study used a case example of 4 Palm Oil Mills (POM), 8 suppliers and 12 time periods. The model is solved using LINGO 19. With the following data in Tables 1-8.

The number of rejected FFBs is uncertain due to the fluctuating nature of the data and the possibility of miscalculation. Thus triangular fuzzy numbers are used where the upper limit is an addition for 15 percent of the rejected quantity, the lower limit is a reduction for 10 percent of the rejected quantity.

1. Vehicle speed is assumed to be ( $Vt$ ) 50 Km/hour.

2. Carbon emission for truck type vehicle ( $TE$ ) is 0.549 Ton CO<sub>2</sub>/Km, assuming the number of trucks passing in one period is 25, then the carbon emission for transportation becomes  $TE=0.549 \times 25$ .

3. Carbon emission for FFB processing TBS ( $PE_{jt}$ ) is assumed to be 1.423 Ton CO<sub>2</sub>/Ton.

4. Carbon emission for CPO storage ( $Iv_E$ ) assumed 0.95 Ton CO<sub>2</sub>/Ton.

Qualitative criteria are used to determine the weight of suppliers, the qualitative criteria used are: Reputation (C1) shows how good the supplier brand, Quality Management (C2) shows how good the supplier's governance. Communication Convenience (C3) shows how good the supplier response is if there is a complaint. Historical Relationship (C4) shows how good the relationship has been established in the past between POM and related suppliers. Quality (C5) shows how good the quality of FFB delivered by the supplier based on the assessment of the decision maker. The steps for solving the model are presented in the following.

**Table 1.** Ordering cost ( $O_{sj}$ ) (Rp) for each period (in units of hundreds of thousands of rupiah)

Supplier	Palm Oil Mills (POM)			
	1	2	3	4
1	8.13	9.24	9.47	5.2
2	8.81	5.66	5.21	7.04
3	7.05	9.3	9.55	9.51
4	6.94	7.03	6.91	6.78
5	9.99	6.38	8.67	5.96
6	6.62	6.25	6.32	7.96
7	9.99	9.09	9.36	8.55
8	6.17	8.78	5	8.71

**Table 2.** Demand of FFB for each period ( $Iv_{jt}$ ) (Ton)

POM	Period											
	1	2	3	4	5	6	7	8	9	10	11	12
1	568	622	447	687	684	546	543	815	466	535	576	710
2	551	580	692	693	529	663	583	575	591	499	618	449
3	497	669	626	653	649	594	728	664	578	589	674	522
4	540	602	547	549	493	660	498	640	765	491	596	607

**Table 3.** Demand of FFB for each POM ( $D_{ji}$ ) (Ton)

POM	Period											
	1	2	3	4	5	6	7	8	9	10	11	12
1	5.148	5.192	5.324	4.950	4.961	5.104	4.983	5.225	4.873	4.940	5.412	4.000
2	4.554	4.961	5.038	4.080	4.230	5.258	5.390	5.071	5.005	4.520	5.093	4.884
3	5.357	4.741	4.220	4.030	4.330	5.324	5.324	4.873	4.873	4.470	4.510	5.269
4	4.796	5.236	4.774	4.830	4.300	4.600	4.970	4.796	5.137	5.049	4.939	4.220

**Table 4.** Accepted FFB from each supplier in previous period ( $qd_{sj}$ ) (Ton)

Supplier	Palm Oil Mills (POM)			
	1	2	3	4
1	4.183	2.096	2.749	4.861
2	3.226	2.856	2.981	3.802
3	4.570	3.155	4.814	4.400
4	4.105	2.749	4.503	2.078
5	2.262	2.702	2.668	4.631
6	4.570	4.135	4.964	4.586
7	2.303	2.382	3.806	4.331
8	3.559	4.353	3.730	2.385

**Table 5.** Rejected FFB in previous period ( $qc_{sj}$ ) in previous period

Supplier	Palm Oil Mills (POM)			
	1	2	3	4
1	453	258	356	400
2	272	453	435	495
3	380	495	220	401
4	437	469	367	330
5	243	222	299	490
6	491	386	327	396
7	427	343	352	437
8	243	325	324	325

**Table 6.** Total production off FFB for each supplier ( $qc_{sj}$ ) (Ton)

Supplier	Period (t)											
	1	2	3	4	5	6	7	8	9	10	11	12
1	19.28	16.77	18.43	16.14	17.74	16.01	16.52	18.06	17.34	16.16	16.24	19.25
2	18.8	17.46	18.51	17.36	18.5	17.56	19.28	17.1	19.36	19.54	19.14	18.02
3	18.54	19.76	18.98	19.43	19.28	17.44	17.79	18.8	18.21	17.94	16.44	19.75
4	19.4	16.4	16.43	17.67	16.54	16.43	19.1	18.74	16.4	16.21	18.58	19.06
5	19.06	19.52	18.62	17.21	17.2	17.9	17.02	19.85	17.72	17.95	17.57	16.23
6	19.99	19.89	18.37	16.06	16.79	18.78	17.08	19.82	18.33	18.06	19.01	19.09
7	17.73	17.05	19.46	17.39	18.11	16.14	17.87	18.45	19.55	18.3	17.38	16.11
8	19.12	16.17	16.89	16.06	17.88	19.31	17.03	18.4	16	18.23	18.66	19.33

**Table 7.** Distance from supplier to POM ( $h_{sj}$ ) (Km)

Supplier	Palm Oil Mills (POM)			
	1	2	3	4
1	8	13	8	10
2	9	29	19	23
3	22	18	16	23
4	21	11	10	12
5	24	16	16	28
6	19	23	28	25
7	26	18	14	26
8	17	6	7	28

**Table 8.** Weight of Supplier which is provided by using AHP

Supplier							
1	2	3	4	5	6	7	8
0.13	0.14	0.15	0.1	0.07	0.17	0.12	0.13

**3.1 Determining supplier weight**

1. Performing a comparison of each criterion to produce a pairwise comparison table as follows Table 9.

**Table 9.** Pairwise comparison

Criteria	C1	C2	C3	C4	C5
C1	1	3	5	3	0.3
C2	0.3	1	0.3	0.3	0.2
C3	0.2	3	1	0.3	0.3
C4	0.3	3	3	1	0.3
C5	3	5	3	3	1

**Table 10.** Pairwise comparison for reputation

C1	P1	P2	P3	P4	P5	P6	P7	P8
P1	1	3	1	0.3	5	0.3	1	3
P2	0.3	1	5	3	1	0.2	3	1
P3	1	0.2	1	0.3	1	1	3	0.2
P4	3	0.3	3	1	0.3	1	0.3	1
P5	0.2	1	1	3	1	0.5	3	1
P6	3	5	1	1	2	1	0.3	0.3
P7	1	0.3	0.3	3	0.3	3	1	1
P8	0.3	1	5	1	1	3	1	1

**Table 11.** Supplier weight

Weight	S1	S2	S3	S4	S5	S6	S7	S8
	0.13	0.14	0.15	0.10	0.07	0.17	0.12	0.13

**Table 12.** Maximum and Minimum value for objective function

No.	Objective Function	Maximum	Minimum
1	Cost	4,059.720	3,513.299
2	Quality	44.70	7.95
3	Delivery Time	3.460	2.266
4	Emission	603.155	521.999
5	Preference	32,777.59	17,686.92

2. Determine the assessment for each alternative (supplier) based on the criteria used. Table 10 shows an example for assessment on reputation.

3. Multiplying the weights on the criteria and the weights on the alternatives for each criterion to produce the supplier's weight as follows in Table 11.

### 3.2 Fuzzy Goal Programming

Solve each objective function separately for minimum and maximum values, so that the results on the tab are obtained. The supplier weights that have been obtained from the AHP

method are used for maximizing the preference of objective function (Table 12).

Performed a comparison for each two objective functions, by making one of the objective functions a constraint. Results are shown in Table 13.

**Table 13.** Payoff table

	Cost	Quality	Delivery Time	Emission	Preference
Cost	3,513.299	12.89	2,681.42	533.377	24,448.66
Quality	3,513.299	7.95	2,265.79	521.999	32,777.59
Delivery Time	3,858.873	11.49	2,265.79	530.975	32,777.59
Emission	3,513.299	7.95	2,265.79	521.999	32,777.59
Preference	3,513.299	7.95	2,265.79	521.999	32,535.90

This table provides a comparative analysis of five key factors such as cost, quality, delivery time, emissions, and preferences that are often considered in real-life decision-making scenarios, such as supply chain management or project planning. For instance, in choosing a supplier, a company must balance the cost of goods (cost), the quality of products received (quality), the time taken for delivery (delivery time), the environmental impact of the supply chain (emission), and

the overall preference or priority given to these factors (preference). The data shows that while one supplier might offer lower costs, they may also have higher emissions or longer delivery times, necessitating a trade-off analysis to determine the best option that aligns with the company's strategic goals and values. Hence, the following membership function is defined as follows:

$$\theta_{cost} = \begin{cases} 0, & \text{if } F_{cost} \geq 3.858.873 \\ \frac{3.858.873 - F_{cost}}{3.858.873 - 3.513.299}, & \text{if } 3.513.299 < F_{cost} < 3.858.873; \\ 1, & \text{if } F_{cost} \leq 3.513.299 \end{cases}$$

$$\theta_{quality} = \begin{cases} 0, & \text{if } F_{quality} \geq 12,89 \\ \frac{12,89 - F_{quality}}{12,89 - 7,95}, & \text{if } 7,95 < F_{quality} < 12,89; \\ 1, & \text{if } F_{quality} \leq 7,95 \end{cases}$$

$$\theta_{time} = \begin{cases} 0, & \text{if } F_{time} \geq 2.681,42 \\ \frac{2.681,42 - F_{time}}{2.681,42 - 2.265,79}, & \text{if } 2.265,79 < F_{time} < 2.681,42; \\ 1, & \text{if } F_{time} \leq 2.265,79 \end{cases}$$

$$\theta_{emission} = \begin{cases} 0, & \text{if } F_{emission} \geq 533.277 \\ \frac{533.277 - F_{emission}}{533.277 - 521.999}, & \text{if } 521.999 < F_{emission} < 533.277; \\ 1, & \text{if } F_{emission} \leq 521.999 \end{cases}$$

$$\theta_{prefer} = \begin{cases} 0, & \text{if } F_{prefer} \geq 24.448,66 \\ \frac{F_{prefer} - 24.448,66}{32.777,59 - 24.448,66}, & \text{if } 24.448,66 < F_{prefer} < 32.777,59; \\ 1, & \text{if } F_{prefer} \leq 32.777,59 \end{cases}$$

Thus the model will be as follows:  $\max \theta = \sum_{k=1}^S \theta_k$

Subject to:

$$\frac{3.858.873 - \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T [P_s \cdot Q_{sjt} + O_{sj} \cdot Z_{sjt} + Plv \cdot Iv_{jt}]}{3.858.873 - 3.513.299} = \theta_1$$

$$\frac{12,89 - \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T \left[ \frac{qd_{sj}}{q_{sjt}} \right] Z_{sjt}}{12,89 - 7,95} = \theta_2$$

$$\frac{2.681,42 - \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T \left[ \frac{\lambda}{C_{st}} \cdot Q_{sjt} + \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T \frac{h_{sj}}{Vt} \cdot Z_{sjt} \right]}{2.681,42 - 2.265,79} = \theta_3$$

$$\frac{533.377 - \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T [TE \cdot h_{sj}] Z_{sjt} + (PE_{jt} \cdot Q_{sjt} + Iv_e \cdot Iv_{jt})}{533.377 - 521.999} = \theta_4$$

$$\frac{F_{prefer} - \sum_{s=1}^S \sum_{j=1}^J \sum_{t=1}^T W_s \cdot Q_{sjt}}{32.777,59 - 24.448,66} = \theta_5$$

$$\sum_{s=1}^S Q_{jst} = D_{jt} - Iv_{jt}$$

$$Q_{jst} \leq C_{st} \cdot Z_{sjt} \quad ; \forall s, j, t$$

$$\sum_{s=1}^S W_s = 1$$

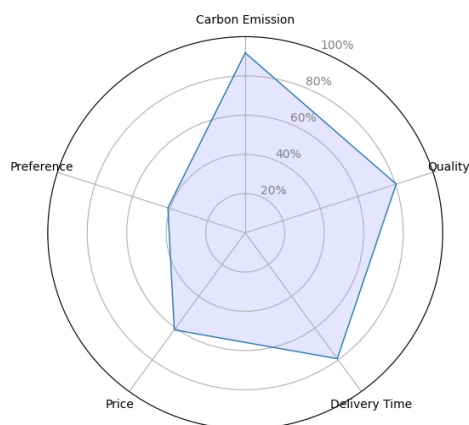
$$I_{fsjt} \geq 0, \quad \forall f, s, j, t$$

$$Z_{fsjt} \in \{0,1\}, \quad \forall f, s, j, t$$

### 3.3 Experimental simulation

We use python to simulate the experimental result in the Figure 1.

#### Satisfaction Levels for Regional Development Criteria



**Figure 1.** Satisfaction levels for regional development

The radar chart effectively visualizes the trade-offs and priorities in regional development decision-making. It shows that while sustainability and operational efficiency are

important, there is a need for better alignment of decision-makers' preferences with these goals. This analysis provides insights into the complexities of regional development and the importance of considering multiple criteria in decision-making processes. Carbon Emission has the highest satisfaction level at 91.76%, indicating that sustainability is highly prioritized in the decision-making process. Quality and Delivery Time also show high satisfaction levels (80.4% and 79.3%, respectively), emphasizing their importance in supplier selection. Price has a moderate satisfaction level of 61.11%, suggesting that while cost is important, it is not the primary driver in this context. Preference has the lowest satisfaction level at 41.18%, indicating a significant mismatch between decision-makers' priorities and the other criteria, or that it may be challenging to balance all criteria simultaneously.

### 4. CONCLUSIONS

Carbon emission had the highest satisfaction level (91.76%) in the survey. This shows that supply chain decision-making prioritizes sustainability. Quality and delivery time satisfaction were high (80.4% and 79.3%), showing their importance in supplier selection. However, price and preference satisfaction were lower at 61.11% and 41.18%. This means that cost is important, but not the key driver in this circumstance. The significant decline in preference satisfaction shows a mismatch between decision-makers' priorities and the other examined factors, or that it may be difficult to balance all the criteria. The results show that palm oil source selection is complicated. They illustrate that while sustainability and operational efficiency are important, decision-makers' preferences must be better aligned with these goals. This analysis illuminates the trade-offs and priorities needed for a sustainable supply chain. The proposed AHP and FGP integrated model has shown trade-offs across criteria, however its limitations and future research prospects must be severely examined. Pairwise comparisons are used to determine criteria weights in the AHP technique, which introduces subjectivity. Decision-makers may make inconsistent assessments, affecting findings robustness. Fuzzy membership functions and parameters might be subjective, but FGP uses fuzzy logic to handle uncertainty. Different definitions of acceptable ranges and satisfaction may yield different results. Delphi method or machine learning algorithms that learn from past decision-making patterns could be used in criteria weighting studies to reduce subjectivity. Real-time data analytics and supply chain management system integration can improve decision-making speed and accuracy. Integration allows continual supplier performance monitoring and appraisal.

### FUNDING

The research was funded by the Research Institute of the Universitas Sumatera Utara (Grant No.: 75/UN5.4.10.S/PPM/KP-TALENTA/RB1/2024).

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## NOMENCLATURE

$s$	FFB supplier, $s=1, 2, 3, \dots, 8$
$j$	Palm Oil Mills (POM), $j=1, 2, 3, 4$
$t$	Period $t=1, 2, \dots, 12$
$P_{st}$	FFB price by supplier- $s$ on period- $t$ (Ton/Kg)
$O_{sjt}$	Ordering cost of POM- $j$ to supplier- $s$ on period- $t$ (Rp)
$Q_{sjt}$	Order allocation of supplier- $s$ for POM- $j$ in period- $t$ (Ton)
$Plv$	Storage cost of CPO (Rp/Ton) CPO
$Iv_{jt}$	Inventory of CPO by POM- $j$ in period- $t$ (Ton)
$qd_{sj}$	Rejected FFB last year (Ton)

$qa_{sj}$	Delivered FFB by supplier-s to POM-j last year (Ton)	$\lambda$	Unit of time period
$Z_{sjt}$	Binary variable (1 if FFB supplied by supplier-S to POM-j on period-t, and 0 otherwise)	$TE$	Carbon emission of transportation (Ton CO <sub>2</sub> /Km)
$C_{st}$	Total production of FFB by supplier-s on period-t (Ton)	$PE_{jt}$	Emission carbon process TBS oleh PKS-j in period-t (Ton CO <sub>2</sub> )
$h_{sj}$	Distance of supplier-f to POM-j (Km)	$Iv_E$	Carbon emission for each ton of CPO inventory CPO (Ton CO <sub>2</sub> )
$V_t$	Speed of transportation (Km/Jam)	$W_s$	Weight of supplier-s