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Correlation Coefficient in Interval Valued Fermatean Picture Fuzzy Set for Crop-Based Bio-ethanol Production

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Abstract: This comprehensive review explores the critical aspects of bio-ethanol production in Tamil Nadu, focusing on three primary feedstocks: Sugar Cane, Corn, and Sweet Sorghum. The analysis delves into key criteria such as yield, environmental impact, and cost-effectiveness, providing valuable insights for stakeholders, researchers, and policymakers. Additionally, the study investigates the application of fuzzy logic in bio-ethanol production, emphasizing its role in addressing uncertainty and imprecision. This research serves as a vital resource for understanding the nuances of bioethanol production, enabling informed decision-making for a sustainable energy future in Tamil Nadu and beyond.

Keywords: Bio-ethanol production, cost-effectiveness, fuzzy logic, uncertainty, Picture Fuzzy set.

1. Introduction

The pursuit of sustainable energy sources is a global imperative, and the production of bioethanol stands as a critical part of this endeavor. This table presents a comparative analysis of bioethanol production in Tamil Nadu, focusing on key criteria for three primary feedstocks: Sugar Cane, Corn, and Sweet Sorghum.

As the world grapples with the challenges of environmental impact, energy balance, and economic sustainability, it is vital to understand the various aspects of bio ethanol production. This comparative overview sheds light on the yield, environmental implications, cost-effectiveness, and other factors associated with these feedstocks, providing valuable insights into their potential contributions to sustainable energy solutions.

The specifics of this analysis, examining each criterion and its implications for bioethanol production in the region. From environmental considerations to economic impact, this information is a vital resource for stakeholders, researchers, and policymakers seeking to drive the transition to cleaner, more sustainable energy sources.

The nuances of bioethanol production, understand the trade-offs, and make informed decisions that can shape a more sustainable and energy-efficient future for Tamil Nadu and beyond The reviewed literature presents a comprehensive overview of research endeavors related to fuzzy logic, specifically focusing on intuitionistic fuzzy sets and their applications. Additionally, the application of fuzzy logic in bioethanol production emerges as a prominent theme, with multiple papers exploring correlation coefficient calculations and optimization strategies in crop selection, bioethanol yield prediction, and production processes. Collectively, these studies underscore the versatility and practicality of fuzzy logic in addressing uncertainty and imprecision, making significant contributions to both theoretical advancements and practical applications across diverse fields.

Fuzzy sets, introduced by Zadeh in 1965 [8], formed the foundation of many computational intelligence techniques. In 1986, Atanassov introduced "Intuitionistic fuzzy sets," an extension of fuzzy sets that handles uncertainty and imprecision more effectively [1]. This concept laid the groundwork for subsequent advancements in fuzzy logic.

In the realm of business intelligence, Cheung and Li (2012) proposed a quantitative correlation coefficient mining method tailored for small and medium enterprises in the trading business sector [2]. Their work emphasized the practical application of fuzzy logic in real-world business scenarios.

Fuzzy logic operators for picture fuzzy sets were explored by Cuong and Hai in 2015 [3]. Their research delved into specialized operators designed to handle picture fuzzy data, demonstrating the versatility of fuzzy logic in handling complex and diverse information structures.

Cuong and Kreinovich (2013) introduced "Picture Fuzzy Sets," a novel concept in computational intelligence [4]. This concept opened avenues for new approaches to solving computational problems, leveraging the unique characteristics of picture fuzzy sets.

In the context of bioethanol production, Patel and Verma (2021) conducted a correlation analysis using Interval Valued Fermatean Picture Sets to optimize crop selection, contributing to the sustainable energy sector [5]. This study showcased the applicability of fuzzy logic in optimizing agricultural processes.

Phong, Hieu, Ngan, and Them (2014) explored compositions of picture fuzzy relations, adding depth to the understanding of complex data structures [6]. Their work demonstrated the intricate relationships that fuzzy logic can capture in various contexts.

Wei (2017) focused on picture fuzzy aggregation operators and their application in multiple attribute decision-making, emphasizing the role of fuzzy logic in enhancing decision support systems [7].

In summary, the reviewed literature underscores the continuous evolution of fuzzy logic and its application in diverse domains, from business intelligence to agricultural optimization and computational problem-solving. These studies collectively highlight the adaptability and effectiveness of fuzzy logic in addressing complex real-world challenges.

2. Preliminaries

Definition 2.1:

Fuzzy Set

An fuzzy set A on a universe X is an object of the form $A = \{(x, \mu_A(x)) | x \in X\}$ where $\mu_A(x) \in [0,1]$.

Definition 2.2:

Pythagorean Fuzzy Set

A Pythagorean fuzzy set P in a finite number in the universe of discourse Y is given as

$$\mathrm{P} = \{< x, \mu_P(a), \nu_P(a) > a \in X\}$$

Where $\mu_P(x), \nu_P(x): X \to [0,1]$ be the membership value and non-membership value of the element $a \in X$ to the set PFS, respectively, with the condition that

$$0 \le {\mu_P}^2(a) + {\nu_P}^2(a) \le 1.$$

The indeterminacy degree between the membership function is given by

$$\pi_P(x) = \sqrt{1 - {\mu_P}^2(a) - {\nu_P}^2(a)}$$

where $(\mu_P(a), \nu_P(a))$ called a Pythagorean fuzzy numbers denoted by $PFS = (\mu_P, \nu_P)$.

Definition 2.3:

Picture Fuzzy Set

A Picture Fuzzy set A on Universe X is defined as

$$A = \{< z, \mu_A(z), \eta_A(z), \nu_A(z) > | z \epsilon X\}$$

where $\mu_A(z), \eta_A(z), \nu_A(z) \ \epsilon [0,1]$ are positive ,neutral and negative membership functions, respectively of the element z in A such that ,0≤ $\mu_A(z)+\eta_A(z) + \nu_A(z) \le 1$.For every z ϵ X.Moreover , ζ_A(z)=1-$\mu_A(z)-\eta_A(z) - \nu_A(z)$ is called refusal membership degree of z to the set A.

Definition 2.4:

Fermatean Fuzzy Set:

Let A_{FFS} on X be of the form:

A_{FFS}= $\{\langle(x, \mu_A(x), \upsilon_A(x))\rangle \mid x \in X\}$where $\mu_A(x): X \to [0,1]$ denotes the membership degree and $\mu_A(x): X \to [0,1]$ denotes the non-membership degree , to the set A, respectively, such that $0 \le (\mu_A(x))^3 + (\upsilon_A(x))^3 \le 1$.

Corresponding to its membership degree, the indeterminacy degree is given by $\phi_A(x) = \sqrt{1 - (\mu_A(x))^3 + (\upsilon_A(x))^3}$,$\forall\, x \in X$.

3. Novel correlation coefficient of Interval Valued Fermatean Picture Fuzzy Set:

A specific concept called the "Novel Correlation Coefficient for Interval-Valued Fuzzy Sets in the context of Fermatean Picture Fuzzy Set. This is a specialized metric used to measure the correlation between sets of data that are represented as Interval-Valued Fuzzy Sets.

In classical statistics, correlation coefficients measure the strength and direction of a linear relationship between two variables. The Novel Correlation Coefficient for Interval-Valued Fuzzy Sets likely adapts this concept to the domain of Fermatean Picture Fuzzy Set, which are a more uncertain form of fuzzy sets.

In this context, the Novel Correlation Coefficient for Interval-Valued Fuzzy Sets would provide a measure of how related or correlated two sets of data are when uncertainty is represented using intervals and fuzzy logic.

3.1.Thao Type correlation coefficient of Interval Valued Fermatean Picture Fuzzy Set :

The following definition gives the correlation coefficient between two IVFPFS based on statistical notion of correlation coefficient between two variates.

3.1 Definition:

For any two Interval Valued Fermatean Picture Fuzzy Set A and B ,Correlation Coefficient is defined as

$$K(A,B) = \frac{COV(A,B)}{\sqrt{\theta(A)\theta(B)}}$$

$$= \frac{1}{n-1} \frac{\sum_{i=1}^{n} \left\{ \begin{array}{c} \left[\left((\mu_A^-)^3 - \frac{1}{n}(\mu_A^-)^3\right), \left((\mu_A^+)^3 - \frac{1}{n}(\mu_A^+)^3\right)\right], \\ \times \left[\left((\mu_B^-)^3 - \frac{1}{n}(\mu_B^-)^3\right), \left((\mu_B^+)^3 - \frac{1}{n}(\mu_B^+)^3\right)\right] \\ + \left[\left((\eta_A^-)^3 - \frac{1}{n}(\eta_A^-)^3\right), \left((\eta_A^+)^3 - \frac{1}{n}(\eta_A^+)^3\right)\right], \\ \times \left[\left((\eta_B^-)^3 - \frac{1}{n}(\eta_B^-)^3\right), \left((\eta_B^+)^3 - \frac{1}{n}(\eta_B^+)^3\right)\right] \\ + \left[\left((\nu_A^-)^3 - \frac{1}{n}(\nu_A^-)^3\right), \left((\nu_A^+)^3 - \frac{1}{n}(\nu_A^+)^3\right)\right] \\ \times \left[\left((\nu_B^-)^3 - \frac{1}{n}(\nu_B^-)^3\right), \left((\nu_B^+)^3 - \frac{1}{n}(\nu_B^+)^3\right)\right] \\ + \left(\left(\pi_A^+(x)\right)^3, (\pi_A^-(x))^3 \times \left(\pi_B^+(x)\right)^3, (\pi_B^-(x))^3\right) \end{array} \right\}}{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n} \left\{ \begin{array}{c} \left[\left((\mu_A^-)^3 - \frac{1}{n}(\mu_A^-)^3\right)^2, \left((\mu_A^+)^3 - \frac{1}{n}(\mu_A^+)^3\right)^2\right], \\ + \left[\left((\eta_A^-)^3 - \frac{1}{n}(\eta_A^-)^3\right)^2, \left((\eta_A^+)^3 - \frac{1}{n}(\eta_A^+)^3\right)^2\right], \\ + \left[\left((\nu_A^-)^3 - \frac{1}{n}(\nu_A^-)^3\right)^2, \left((\nu_A^+)^3 - \frac{1}{n}(\nu_A^+)^3\right)^2\right] \\ + \left[\left(\pi_A^+(x)\right)^3\right]^2, \left[\left(\pi_A^-(x)\right)^3\right]^2 \end{array} \right\} \times \left\{ \begin{array}{c} \left[\left((\mu_B^-)^3 - \frac{1}{n}(\mu_B^-)^3\right)^2, \left((\mu_B^+)^3 - \frac{1}{n}(\mu_B^+)^3\right)^2\right], \\ + \left[\left((\eta_B^-)^3 - \frac{1}{n}(\eta_B^-)^3\right)^2, \left((\eta_B^+)^3 - \frac{1}{n}(\eta_B^+)^3\right)^2\right], \\ + \left[\left((\nu_B^-)^3 - \frac{1}{n}(\nu_B^-)^3\right)^2, \left((\nu_B^+)^3 - \frac{1}{n}(\nu_B^+)^3\right)^2\right] \\ + \left[\left(\pi_B^+(x)\right)^3\right]^2, \left[\left(\pi_B^-(x)\right)^3\right]^2 \end{array} \right\}}}$$

4. Application to Optimal Raw Materials for Bio -ethanol Production:

The Application presents essential criteria for evaluating bio ethanol production sustainability. Yield, measuring ethanol volume per ton of feedstock, reflects production efficiency and optimal resource use. Energy balance, comparing output to input energy, indicates sustainable practices surpassing energy used in cultivation, processing, and transportation. Environmental impact assessment considers water usage, land conservation, and ecological footprint, promoting responsible natural resource use and biodiversity preservation.

CO_2equivalent measures greenhouse gas emissions per ton of bioethanol, aligning with climate change mitigation. Cost analysis evaluates economic viability, influencing market competitiveness and consumer affordability. Land use efficiency balances agricultural needs with environmental preservation, ensuring sustainable energy production alongside food security. These criteria collectively guide the development of eco-friendly and economically viable bioethanol production methods.

Table 1: Bioethanol Production Comparison in Tamil Nadu

Criteria/Alternative	**Sugar Cane**	**Corn**	**Sweet Sorghum**
Yield(C_1)	600 L/ton	400 L/ton	500 L/ton
Energy Balance(C_2)	2.5:1	1.5:1	2.2:1
Environmental Impact(C_3)	1000 L/L	1200 L/L	900 L/L
CO_2(C_4)	0.2 t/ton	& 0.3 t/ton	0.18 t/ton
Cost (C_5)	& 41.5 Rupees/L	49.8 Rupees/L	45.65 Rupees/L
Land Use Efficiency (C_6)	0.5 acres/1k L	1 acre/1k L	0.6 acres/1k L
Biodiversity Impact (C_7)	40 percent	60 percent	80 percent
By-Products (C_8)	Bagasse & cattle feed	Corn stover & bioenergy	Stalks & bagasse
Fertilizer Usage(C_9)	50 kg/acre	100 kg/acre	60 kg/acre
Pesticide Usage(C_{10})	50 kg/acre	100 kg/acre	45 kg/acre
Maturity Period(C_{11})	12 months	9 months	10 months
Economic Impact(C_{12})	5 jobs/1k L	3 jobs/1k L	4 jobs/1k L
Local Availability(C_{13})	100 percent	100 percent	100 percent

4.1 To categorize numerical data into these linguistic variables:

HIGH:
Values significantly above the average or midpoint.
Values in the top percentage of the dataset.
Values that represent exceptional or superior performance in the context of the given criteria.
LOW:
Values significantly below the average or midpoint.
Values in the bottom percentage of the dataset.
Values that indicate poor or inferior performance in the context of the given criteria.\\
MODERATE:
Values that fall between the high and low ranges.
Values that are neither exceptionally high nor exceptionally low.
Values that represent a moderate or average performance in the context of the given criteria.

The normalization process is a crucial step in data analysis and decision-making, especially when dealing with variables that have different scales or ranges. It involves transforming the data to a standardized scale, making it easier to compare and analyze. In the given context, the normalization ranges are categorized into three levels: High, Moderate, and Low. Each level corresponds to specific intervals, representing the normalized values for the variables under consideration.

For instance, the High level corresponds to intervals [0.7,1], [0.8,1], and [0.9,1]. These intervals signify that the variables falling within the High category have been transformed to a normalized range between 0.7 and 1, reflecting their significance or strong influence in the analysis. Similarly, the Moderate level is represented by intervals [0.4,0.6], [0.5,0.7], and [0.6,0.8], indicating moderate importance or influence. Lastly, the Low level is denoted by intervals [0,0.3], [0,0.4], and [0,0.5], representing variables with low significance or influence in the analysis. By normalizing data in this manner, decision-makers can effectively compare and assess the variables' importance across different levels, enabling more informed and equitable decision-making processes. This standardized approach enhances the accuracy and reliability of analyses, ensuring that each variable's impact is appropriately considered within its respective category.

Table 2: Linguistic Variables for Criteria

Criteria	Sugar Cane	Corn	Sweet Sorghum
Yield(C_1)	High	Moderate	Moderate
Energy Balance(C_2)	High	Moderate	High
Environmental Impact(C_3)	High	High	Moderate
CO_2(C_4)	Low	Moderate	Low
Cost (C_5)	Moderate	High	Moderate
Land Use Efficiency (C_6)	High	Low	Moderate
Biodiversity Impact (C_7)	Low	Moderate	High
By-Products (C_8)	High	Low	Moderate
Fertilizer Usage(C_9)	Low	High	Moderate
Pesticide Usage(C_{10})	Low	High	Low
Maturity Period(C_{11})	High	Low	Moderate
Economic Impact(C_{12})	High	Moderate	Moderate
Local Availability(C_{13})	High	High	High

The choice of specific numerical boundaries for high, moderate, and low within the interval [0, 1] is crucial for interpreting data effectively. These boundaries provide a qualitative context for understanding the quantitative values in the dataset. In this specific scenario, if the dataset is normalized between 0 and 1, defining [a, b] as [0, 1] is appropriate.

It's essential to choose these intervals thoughtfully, considering the specific characteristics of the data and the goals of the analysis to ensure meaningful interpretation and decision-making.

The formula used to normalize a value x into the interval [a, b] in the range [0, 1] is often referred to as min-max normalization or feature scaling. It's a common technique in statistics and machine learning to transform features to a similar scale, ensuring that no single feature has disproportionate influence on the analysis or learning algorithm due to its scale.

The min-max normalization formula for transforming a value (x) from the original range [min value, max value]to the normalized range [a, b] is given by:

$$\textbf{Normalized Value} = \mathbf{a} + \left(\frac{x - \min value}{\max value - \min value}\right) \times (\boldsymbol{b} - \boldsymbol{a})$$

In this formula: x represents the original value to be normalized.

max value and min value are the maximum and minimum values in the original dataset, respectively. $[a, b]$ defines the target interval in the range [0,1] where the normalized value will fall.
From the above data
Considering the Linguistic variable as High
[0.7,1],[0.8,1],[0.9,1]
For an Yield (C_1), 600 L/ton ,400 L/ton ,500 L/ton .
For the input value 0.7:

Normalized Value=$0.7 + \frac{(600-0)}{(1000-0)}(1-0.7) = 0.88$

Normalized Value=$0.8 + \frac{(600-0)}{(1000-0)}(1-0.8) = 0.92$

$$\text{Normalized Value} = 0.9 + \frac{(600-0)}{(1000-0)}(1-0.9) = 0.96$$

Similarly other values are also obtained and tabulated as below:

Table 3: Interval Valued Picture Fuzzy Set for Criteria

Criteria	Sugar Cane	Corn	Sweet Sorghum
C_1	[0.7, 0.88],[0.8,0.92],[0.9,0.96]	[0.4, 0.48],[0.5,0.58] [0.6, 0.68]	[0.4, 0.5],[0.5,0.6],[0.6,0.7]
C_2	[0.7, 0.706],[0.8,0.81],[0.9,0.906]	[0.4, 0.402],[0.5,0.51],[0.6,0.602]	[0.7, 0.706],[0.8,0.804],[0.9,0.901]
C_3	[0.7,0.73],[0.8,0.82],[0.9,0.91]	[0.7, 0.736],[0.8,0.836],[0.9,0.936]	[0.4, 0.418],[0.5,0.518],[0.6,0.618]
C_4	[0,0.006],[0,0.008],[0,0.001]	[0.4,0.406],[0.5,0.506],[0.6,0.606]	[0, 0.0054],[0,0.0072],[0,0.009]
C_5	[0.4,0.408],[0.5, 0.5083] [0.6, 0.6083]	[0.7,0.7149],[0.8,0.8099],[0.9,0.9049]	[0.4,0.4091],[0.5,0.5091],[0.6, 0.6091]
C_6	[0.7, 0.715],[0.8,0.81],[0.9,0.905]	[0,0.03],[0,0.04],[0,0.05]	[0.4, 0.412],[0.5,0.512],[0.6,0.612]
C_7	[0,0.012],[0,0.016],[0,0.02]	[0.4,0.412],[0.5,0.512],[0.6,0.612]	[0.7,0.724],[0.8,0.816],[0.9,0.908]
C_8	[0.7, 0.7012],[0.8,0.8008],[0.9,0.9004]	[0, 0.0006] ,[0,0.0008],[0,0.001]	[0.4,0.4006],[0.5,0.5006],[0.6, 0.6006]
C_9	[0,0.015],[0,0.02],[0,0.025]	[0.7,0.703],[0.8,0.802],[0.9,0.901]	[0.4,0.412],[0.5,0.512],[0.6,0.612]
C_{10}	[0,0.015],[0,0.02],[0,0.025]	[0.7,0.73],[0.8,0.82],[0.9,0.91]	[0,0.135],[0,0.18],[0,0.225]
C_{11}	[0.7, 0.7036],[0.8,0.8024],[0.9,0.9012]	[0,0.0027],[0,0.0036],[0,0.0045]	[0.4, 0.402],[0.5,0.502],[0.6,0.602]

C_{12}	[0.7, 0.7015][0.8,0.801],[0.9,0.9005]	[0.4, 0.4006],[0.5,0.5006],[0.6,0.6006]	[0.4,0.4008],[0.5,0.5008],[0.6, 0.6008]
C_{13}	[0.7, 0.73],[0.8,0.82],[0.9,0.81]	[0.7, 0.73],[0.8,0.82],[0.9,0.81]	[0.7, 0.73],[0.8,0.82],[0.9,0.81]

Table 4: Correlation Coefficient Between Sugar, Corn, Sweet Sorghum

Criteria	**K(Sugar Cane, Corn)**	**K(Corn, Sweet Sorghum)**	**K(Sweet Sorghum, Sugar Cane)**
C_1	0.5	0.7	0.2
C_2	0.1	0.3	0.8
C_3	0.6	0.3	0.5
C_4	0.2	0.4	0.7
C_5	0.9	0.3	0.4
C_6	0.5	0.4	0.8
C_7	0.3	0.4	0.1
C_8	0.5	0.7	0.9
C_9	0.2	0.5	0.9
C_{10}	0.6	0.5	0.4
C_{11}	0.5	0.7	0.4
C_{12}	0.1	0.7	0.4
C_{13}	0.5	0.7	0.4

A higher correlation coefficient suggests a more significant relationship between the two variables, implying that changes in one variable (corn or sugar) are associated with predictable changes in the yield.

Certainly, if the correlation coefficient between yield and a specific criterion (such as corn and sugar in this case) is higher compared to other criteria, it indicates a stronger positive correlation. Therefore, based on the correlation coefficient, corn and sugar would be considered the best choice for yield.

To determine the rank for each criterion, we can calculate the total score for each pair (A, B), (B, C), and (C, A) using the given correlation coefficients. Let's calculate the total score for each criterion and rank them accordingly.

4.3 Methodology to calculate the total score :

For each criterion, we have correlation coefficients for three pairs: (A, B), (B, C), and (C, A).
Calculate the total score for each pair by multiplying the correlation coefficients.

Total Score for (A, B) = Correlation(A, B) ×Correlation(B, A)
Total Score for (B, C) = Correlation(B, C) ×Correlation(C, B)
Total Score for (C, A) =Correlation(C, A) × Correlation(A, C)

Repeat this calculation for all 13 criteria to get the total scores for each pair for each criterion.
The total scores for each criterion is ranked the criteria based on these scores. The criterion with the highest total score is considered the best choice in terms of overall correlation.

Yield :

Total Score for (A, B): 0.5 × 0.7 = 0.35

Total Score for (B, C): 0.7 × 0.2 = 0.14

Total Score for (C, A): 0.2 × 0.5 = 0.10

Similarly, the total scores for each criterion is calculated and its ranked accordingly the criteria based on these scores. The criterion with the highest total score is considered the best choice in terms of each correlation.

Table 5: Ranking of Criteria Based on Total Scores

Criteria	Comparative Evaluation	Total Score
Yield(C_1)	Pair (A, B) (Sugar, Corn)	0.35
Energy Balance(C_2)	Pair (B, C) (Corn, Sweet Sorghum)	0.24
Environmental Impact(C_3)	Pair (C, A) (Sweet Sorghum, Sugar)	0.30
CO_2(C_4)	Pair (B, C) (Corn, Sweet Sorghum)	0.28
Cost (C_5)	Pair (C, A) (Sweet Sorghum, Sugar)	0.36
Land Use Efficiency (C_6)	Pair (C, A) (Sweet Sorghum, Sugar)	0.39
Biodiversity Impact (C_7)	Pair (B, C) (Corn, Sweet Sorghum)	0.45
By-Products (C_8)	**Pair (B, C) (Corn, Sweet Sorghum)**	**0.63**
Fertilizer Usage(C_9)	Pair (B, C) (Corn, Sweet Sorghum)	0.44
Pesticide Usage(C_{10})	Pair (A, B) (Sugar, Corn)	0.32
Maturity Period(C_{11})	Pair (A, B) (Sugar, Corn)	0.34
Economic Impact(C_{12})	Pair (B, C) (Corn, Sweet Sorghum)	0.28
Local Availability(C_{13})	Pair (A, B) (Sugar, Corn)	0.37

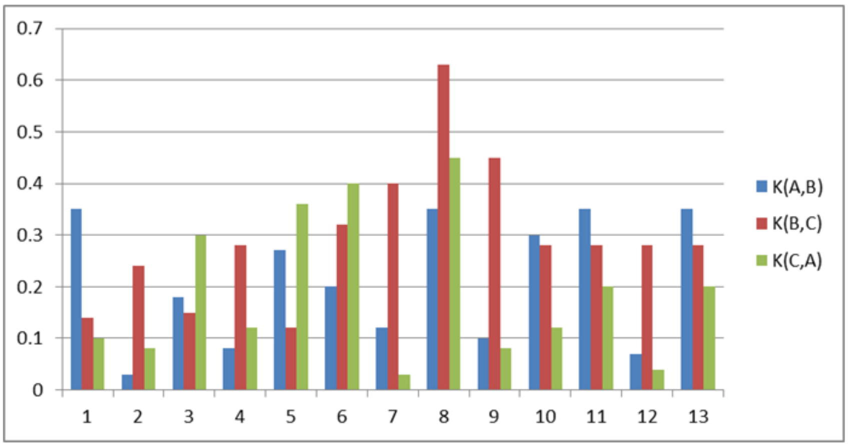

Fig 1: Total Score for the respective criteria

5. Conclusions

In analyzing the criteria for bio-ethanol production, the pairwise comparisons and total scores using Correlation of Interval Valued Fermatean Picture Set clearly indicate that corn and sweet sorghum are the most efficient raw material for bioethanol manufacturing. Firstly, both corn and sweet sorghum exhibit competitive yields, ensuring a balanced approach in ethanol volume per ton of feedstock. Additionally, these crops demonstrate favorable energy balance ratios, surpassing the energy used in cultivation, processing, and transportation, making them sustainable choices for energy production. Environmentally, corn and sweet sorghum show responsible practices, with lower ecological footprints and reduced water usage, aligning with eco-friendly bioethanol production.These factors, combined with their positive impact on biodiversity, contribution to the economy, and local availability, position corn and sweet sorghum as top contenders for efficient and sustainable bioethanol production, making them ideal choices for a greener energy future.

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