International Journal of Mathematical, Engineering and Management Sciences
Vol. 11, No. 2, 971-990, 2026
https://doi.org/10.33889/IJMEMS.2026.11.2.040

Generalized Fuzzy TOPSIS Approach for Solving Fuzzy Multi-Criteria Decision-Making Problem: A Study on Food Processing

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(Received on June 29, 2025; Revised on November 18, 2025; Accepted on February 13, 2026)

Abstract
The fuzzy multi-criteria decision-making (FMCDM) problem can be solved using a variety of techniques, one of which is FTOPSIS (Fuzzy Technique for Order Preference by Similarity to Ideal Solution). FTOPSIS are widely used to handle uncertainty in complex evaluation problems where linguistic judgments are involved. The linguistic values are used to determine all of the criterion fuzzy weights and alternative values in FTOPSIS method. The main aim of this paper is utilizing the generalized fuzzy TOPSIS approach to assess the current status and trends of the food processing industry in Odisha. It seeks to invest the money in different food processing industry for industry's growth and development. The results of the food processing industry have been described using the generalized FTOPSIS method. The best food processing industry can be identified using this method based on various criteria. The recommended method is compared to the suggested method to determine its effectiveness. We solve the FMCDM problem using generalized FTOPSIS approach, for greater efficiency. Moreover, engaging with industrial firms can enhance the decision-making process by identifying the most appropriate and effective alternative.

Keywords- Closeness coefficients, Decision support system, Food processing industry, FMCDM, FTOPSIS.

Abbreviations
AHP: Analytical hierarchy process
FAHP: Fuzzy analytical hierarchy process
DEA: Data Envelopment Analysis
DSS: Decision support system
FDS: Fuzzy decision-method
MADM: Multi attribute decision-making
MCDM: Multi-criteria decision making
FMCDM: Fuzzy multi-criteria decision making
MODM: Multi-objective decision-making
SAW: Simple additive weighting
FSAW: Fuzzy simple additive weighting
TOPSIS: Technique for order preference by similarity to ideal solution
Fuzzy TOPSIS: Fuzzy technique for order preference by similarity to ideal solution
FS: Feature selection
GIS: Geographical information system

PSO: Particle swarm optimization
DG: Distributed generation
FMPSO: fuzzy-dominance based many-objective particle swarm optimization
PIS: Positive ideal solution
NIS: Negative ideal solution
FPIS: Fuzzy positive ideal solution
FNIS: Fuzzy negative ideal solution

List of Symbols
$\mu_{\tilde{F}}(x)$: Fuzzy membership function
Δ: Fuzzy decision matrix
F_{ij} : Element of fuzzy decision matrix, where *i* = set of alternatives, and *j* = set of criteria
$\widehat{F_{ij}}$: Normalized fuzzy matrix
$\widehat{w_{ij}}$: Weighted values
$\widehat{H_{ij}}$: Weighted normalized fuzzy matrix
$\hat{A}^{+}$: Fuzzy positive ideal solution
$\hat{A}^{-}$: Fuzzy negative ideal solution
d_i^{+} : Distance from FPIS
d_i^{-}: Distance from FNIS
CC_i: Closeness coefficient

1. Introduction

Crisp data are not enough to accurately simulate real-life events in all situations. Although they are typically ill-defined and challenging to quantify, preferences play a part in human judgements (Zadeh, 1965). In the past 40 years, fuzzy theory has established a research regulation in the pair of approaches and concepts that have been used to solve problems involving decision-making (Zimmermann, 1987). According to several sources, decision-making is the process of determining which option from all of the available options is the best. The objectives and constraints define classes of options with definite boundaries. The first fuzzy theory in decision-problems was introduced by Bellman and Zadeh (1970). They initially created fuzzy sets as a way to represent and work with data that wasn't precise but was rather ambiguous. Vague values, uncertain values, and fuzzy set theory are applied in each option's calculations with respect to several criteria (Hwang and Yoon, 2012). Multi-criteria decision-making problem (MCDM) is the name given to this problem when it is paired with several criteria. Fuzzy decision-method (FDM), a contemporary decision support system (DSS), is created by merging fuzzy set theory and MCDM (Wang et al., 2005). In the case of linguistic variables, this technique must distinguish between the many possibilities in light of the specific criteria. In decision-making problems where it is necessary to choose the best alternatives for many criteria, multi-criteria decision-making approaches are frequently utilized.

A MCDM problem can be divided into two categories, such as multi-attributes decision-making (MADM) and multi-objective decision-making (MODM) (Mansour et al., 2019). When fuzzy values are used, this MCDM problem is generalized into an FMCDM problem. Then, Chen and Hwang (1992) have authorized a contemporary fuzzy multi-criteria decision-making (FMCDM). In the case of the MCDM problem, the production rating and the number of criteria it contains are presented by rigid values, however in the case of the fuzzy MCDM problem, all values are represented by fuzzy numbers in linguistic terms. First, we must generalize straightforward MCDM approaches to encompass fuzzy values in order to handle FMCDM problems. We have also presented a new FMCDM method. The solutions to these FMCDM issues were determined using a variety of methods, including TOPSIS, AHP, fuzzy TOPSIS, fuzzy AHP (Chang, 1996; Wang and Lee, 2007) and SAW with its fuzzy values (Triantaphyllou and Lin, 1996; Piasecki et al., 2019).

The TOPSIS method is one of these well-liked methods for MCDM problem. The majority of TOPSIS techniques can be easily modified for usage in a fuzzy environment, with the exception of the max and min operations required to find the ideal solution and the negative ideal solution (Pei, 2015). This approach has a number of advantages, such as simplicity, logic, comprehensibility, good processing efficiency, and the capacity to assess the relative performance of each option, which is expressed in an easy-to-understand mathematical manner. The author then invited users to submit (linguistic) ratings of these organizations based on the selected criteria by utilizing the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (FTOPSIS) approach to solving the FMCDM problem (Jahanshahloo et al., 2006) for the investigation of money in best development of food processing industry in Odisha.

Although India has a strong agricultural foundation, there is a significant amount of food waste and very little food product processing. Only 10% of India's food is now processed to consumable levels due to the little size of the processing industry in the nation. India's contribution to global processed food exports has stayed relatively stable at 1.5%, or $3.2 billion. In addition, India produces a wide range of fruits, vegetables, and other food items from temperate to tropical regions. The preservation and efficient use of fruits, vegetables and other food companies are significantly impacted by food processing. India has a lot of promise for the food processing business, which creates a strong connection between farmers and consumers, because of its strong agricultural foundation, diversity of climatic zones, and rapid economic expansion. This paper aims to analyze the current trends and the overall status of the food processing industry in Bhubaneswar, Odisha, India. It seeks to invest the money in different food processing industry for industry's growth and development. The results of the best food processing industry have been described using the generalized fuzzy TOPSIS method. The best food processing industry can be identified using this method based on various criteria.

In this paper, we used the linguistics value of fuzzy weights in triangular fuzzy number for finding the set of alternative and criterion under the basis of expert's opinion. The main aim of this paper is to analyze the investigation of money in different food processing industries for the best industry's growth and development. The results of the food processing industry have been described using the generalized fuzzy TOPSIS method. The best food processing industry can be identified using this method based on various criteria with the two weighted values in different thought of experts. Then, to calculate the positive and negative optimal solutions of each alternative in each of two weights of criterion under the fuzzy TOPSIS approach. After that, to obtain the separation distance of each alternative from both positive as well as negative ideal solutions for two determined weights. Using this distance, then to calculated the two different closeness coefficient values of each option and the final closeness values under the basis of average. After that, it is time to classify the ranking of each alternative using overall performance indices.

This paper describes a systematic technique for expanding fuzzy TOPSIS procedures, where the values, in the case of a fuzzy triangular number, are specified by linguistic variables. This method can be used to solve the MCDM problem in a hazy situation. In Section 2, we discuss the related work of FMCDM problems. In Section 3, the author goes over the basic definitions of MCDM and FMCDM issues. The fuzzy TOPSIS methodology is shown in the following Section 4. In Section 5, they talk about a case analysis of food processing company using fuzzy TOPSIS technique. Then they discuss the comparison analysis of the propose method with the suggested method in Section 6. Next, Section 7 contained the concluding remarks of the paper and some future scope.

2. Literature Review

The MCDM technique, which has been successfully used to address a number of issues, is at the focus of the research that is planned. The traditional MCDM problem is analyzing the problems and selecting the optimal course of action using numerous methodologies, including TOPSIS, AHP, and SAW, among others. The MCDM problem is then transformed into the FMCDM problem, which handles the problems and chooses the best solution using a range of methods, such fuzzy TOPSIS, fuzzy AHP, etc., using linguistics variables. This extended TOPSIS approach with hazy value is used to tackle the MCDM problem (Wang et al., 2005). The analysis of the MCDM problem in group decision making using the enhanced TOPSIS method came next (Jahanshahloo et al., 2006). Then, in FMCDM with group decision-making, utilize the generalized TOPSIS technique (Hwang and Yoon, 2012). This TOPSIS method is also used in multi-granularity problem using the linguistics data for group decision making (Fan and Liu, 2010).

Now to construct the project selection in FMCDM problem using fuzzy TOPSIS technique, which was introduced in (Tan et al., 2010). This fuzzy TOPSIS method are used to determining the positive and negative extreme solutions in fuzzy MCDM problem under the operations of min-max (Wang, 2011). Then to discussed the FMCGDM problem in supplier selection under the presence of simulation based fuzzy TOPSIS method (Zouggari and Benyoucef, 2012). The TOPSIS method are also introduced in multi attribute decision-making (MADM) with the linguistics data (Parida and Sahoo, 2013). Then the FMCGDM problem are also introduced in social influence with the vague data (Capuano et al., 2017). In support waste management, MCDM problem are also used with fuzzy TOPSIS technique (Coelho et al., 2017). Then this method is described in the evaluation of performance reverse logistics in social commerce (Hui and Silvana, 2018). Now for determination of closeness coefficients, the generalized fuzzy TOPSIS method are established in FMCDM problem (Dwivedi et al., 2018). Then, to use the gradual weight-based method in multi objective decision-making problem under the basis of ant colony approach. After that, feature selection (FS) to produce a more accurate and swift classification model in FMCDM problem. So, for feature selection, the author here used fuzzy ensemble technique (Ghosh et al., 2019).

The performance of Colombian is evaluated using the MCDM hybrid problem in (Yazdi et al., 2020). Then FTOPSIS technique are also described in the selection of sustainable construction using geopolymeric mortars (Saeli et al., 2020). In supply chain, fuzzy TOPSIS method are discussed for finding the best food (Tomasiello and Alijani, 2021). Then this TOPSIS method are also introduced in the MCDM problems using fuzzy values (Parida et al., 2021). According to this viewpoint, a new multi-objective sine-cosine algorithm is suggested for the best DG placement in radial distribution systems with the least amount of total active power loss, the highest amount of voltage stability index, the least amount of annual energy loss costs, and the least amount of pollutant gas emissions while still operating within the bounds of the system and the DG (Raut and Mishra, 2021).

Then used the probabilistic hesitant fuzzy value for calculating the MCDM problem under the presence of linguistics data (Wang et al., 2022). The rough valued TOPSIS method are discussed in the selection of clean energy in green ships under the basis of group decision making in FMCDM problem (Xuan et al., 2022). In this MCDM problem, the ranking performance value are determined by hybrid MCDM method under the uncertainty data (Yazdi et al., 2022a). The fuzzy TOPSIS approach are used in MCDM problem for selecting the supplier in oil gas industry (Yazdi et al., 2022b). Then, the TOPSIS method and dynamics model are used to simulate the water resources carrying capacity of hangbu river (Liu et al., 2022). In order to maximize total system reliability while staying within resource constraints, this paper investigates the optimization of system reliability in a modular redundancy allocation issue in crisp and intuitionistic fuzzy atmospheres (Paramanik et al., 2022).

In fuzzy environment, TOPSIS method are used in MADM problem with linguistic terms for determination of the decision matrix (Baral et al., 2023). The operational and applications of cohesive fuzzy set are used for determining the FMCDM problem in solar electromagnetic signal (Xue et al., 2023). Then using input output data identified system, author present a novel method for building an interval-valued fuzzy model (IVFM) of Takagi -Sugano (TS) (Bouhentala et al., 2023). The quality function development and FTOPSIS are used in MCDM technique for the evaluation of supplier (Sharma and Tripathy, 2023). This MCDM problem are evaluated by the generalized trapezoidal fuzzy value using the measure of distance (Dutta and Borah, 2023). MCDM techniques are used in this work to identify the critical aspects influencing women's empowerment in sports, politics, journalism or media, and technology in India. These techniques can also be used to other important areas of women's empowerment research. The same MCDM problem are used in online shopping for website selection under the basis of hendecagonal fuzzy number (Revathi and Valliathal, 2023).

After that, the generalized fuzzy TOPSIS method are discussed in MCDM problem for calculating the temperature in Bhubaneswar city (Sahoo et al., 2023). Finally, this MCDM problem are also solved by neutrosophic fuzzy using trapezoidal fuzzy number under the linguistic data (Prakash and Suresh, 2024). Then, author discussed the fuzzy MCDM problem using min-max operations of fuzzy TOPSIS approach for the selection of optimal college location (Sahoo et al., 2024). Then the fuzzy TOPSIS and TOPSIS method are also explained in the evaluation of sustainable water management in the FMCDM problem (Han et al., 2025). In circular supply chain, the role of environmental sustainability and digital technology are also expressed with the help of fuzzy TOPSIS method (Duan et al., 2025). Then the MCDM problems are solved by the basis of entropy weight method in the selection of e-waste recycling partner (Baral et al., 2025). Then Saikia et al. (2020) presented advanced distance measures between two intuitionistic hesitant fuzzy sets. Additionally, a novel aggregation operator for material selection problems based on interval-valued Pythagorean fuzzy soft sets was recently developed. This operator increases the reliability of multi-criteria decision-making processes and handles vagueness better (Sahoo et al., 2025).

In this study, we employ the generalized FTOPSIS method to address the FMCDM problem by determining the criterion weights based on experts' opinions, thereby ensuring the robustness and effectiveness of the proposed approach. Among the reviewed studies, those most relevant to our work are summarized in **Table 1**.

Table 1. Comparative analysis with existing methods.

Authors	TOPSIS	FTOPSIS	AHP	Min-max operation	Generalized FTOPSIS
Han et al. (2025)	✓	✓	×	×	×
Sahoo et al. (2024)	×	✓	×	✓	×
Sharma and Tripathy (2023)	×	✓	×	×	×
Baral et al. (2023)	✓	×	×	×	×
Liu et al. (2022)	✓	×	×	×	×
Xuan et al. (2022)	✓	×	×	×	×
Proposed Work	×	✓	×	×	✓

3. Preliminaries

This section is followed by a discussion of some basic definitions of fuzzy sets.

3.1 Definitions

Fuzzy set: A fuzzy set $\hat{\mathcal{F}}$on X is designated by membership function $\mu_{\hat{\mathcal{F}}}(x)$, which connect between the function mappings from each factor to the range of $[0, 1]$. It is designated as

$$\hat{\mathcal{F}} = \{(x, \mu_{\hat{\mathcal{F}}}(x)), x \epsilon X\} \tag{1}$$

where, $\mu_{\hat{\mathcal{F}}}(x): X \to [0,1]$.

Triangular fuzzy number: The membership function of the triangular fuzzy number $[f_1, f_2, f_3]$ of a fuzzy set $\hat{\mathcal{F}}$ is represented as

$$\mu_{\hat{\mathcal{F}}}(x) = \begin{cases} 0, \quad x \leq f_1 \; or \; x \geq f_3 \\ \frac{x-f_1}{f_2-f_1}, f_1 \leq x \leq f_2 \\ \frac{f_3-x}{f_3-f_2}, f_2 \leq x \leq f_3 \end{cases} \tag{2}$$

where, f_2 is the center(peak) with a membership degree of one and f_1 and f_3 are the lower and upper borders with membership degrees of zero, respectively. The membership function of a triangular fuzzy number is linear on both sides of the peak.

Definition: The distance between two triangular fuzzy numbers is

$$d_b(\widehat{\mathcal{N}}_1, \widehat{\mathcal{N}}_2) = \sqrt{\frac{1}{3}[(\hat{l}_1 - \hat{l}_2)^2 + (\widehat{m}_1 - \widehat{m}_2)^2 + (\hat{n}_1 - \hat{n}_2)^2]} \tag{3}$$

3.2 Properties of Triangular Fuzzy Numbers

***Property* 1**

Let $\hat{F} = [f_1, f_2, f_3]$ and $\hat{G} = [g_1, g_2, g_3]$ be two triangular fuzzy numbers of two different fuzzy sets. Then the following properties are holds:

- $\hat{F} + \hat{G} = [f_1 + g_1, f_2 + g_2, f_3 + g_3]$
- $\hat{F} - \hat{G} = [f_1 - g_3, f_2 - g_2, f_3 - g_1]$
- $\hat{F} \times \hat{G} = [f_1 \times g_1, f_2 \times g_2, f_3 \times g_3]$
- $\hat{F} \div \hat{G} = [f_1 \div g_3, f_2 \div g_2, f_3 \div g_1]$
- $\alpha\hat{F} = [\alpha f_1, \alpha f_2, \alpha f_3]$, $\alpha \geq 0$.
- $\hat{F}^{-1} = \left[\frac{1}{f_3}, \frac{1}{f_2}, \frac{1}{f_1}\right]$
- $(-1)\hat{F} = [-f_3, -f_2, -f_1]$ (Symmetric image)

***Property* 2**

The addition, subtraction, and symmetric image of triangular fuzzy number is also a triangular fuzzy number.

***Property* 3**

The multiplication or division between two triangular fuzzy numbers are not triangular fuzzy numbers. Although the division and multiplication of triangle fuzzy numbers are defined, the product of the lower limits, peaks, and upper bounds may produce a non-linear combination that is not a triangular fuzzy number.

TOPSIS Method

A multi-criteria decision-making (MCDM) method known as TOPSIS (Technique for order preference by similarity to ideal solution) evaluates and ranks a set of alternatives based on multiple criteria. It was first introduced in 2012 by Hwang and Yoon. It is frequently used to resolve ranking issues in multi criteria decision-making problems using precise and crisp values. This approach is based on the best option that has been shown to be the closest to PIS and the furthest from NIS. It helps decision-makers identify the best option by comparing each alternative to an ideal solution.

Fuzzy TOPSIS Method

The fuzzy technique for order performance by similarity to ideal solution (Fuzzy TOPSIS) is one particular approach for identifying MCDM issues using fuzzy, uncertainty and imprecision values. It uses fuzzy numbers to represent criteria, allowing for more flexible, realistic decision-making when data is vague or uncertain. The fundamental goal of this process is to select the best alternative, which must have the shortest distance from FPIS (solutions that minimize cost criteria and maximize benefit criteria); and the furthest distance from FNIS (solutions that maximize cost criteria and minimize benefit criteria).

4. Problem Description

This section covers the briefly discussion of Fuzzy TOPSIS method in MCDM problem under the two calculated weights by using the expert's suggestion.

This subsection covers a methodology on fuzzy multi-criteria decision-making problem under generalized fuzzy TOPSIS method. This generalized fuzzy TOPSIS method is the extension of the fuzzy TOPSIS method. Let $A_1, A_2, \dots, A_m, i = 1\ to\ m$ be the set of alternatives under the criterion $C_1, C_2, \dots, C_n,\ j = 1\ to\ n\ and\ F_{ij} = (f_{1ij} f_{2ij}, f_{3ij})$ be an elements of the group decision matrix Δ of m alternatives with respect to n criterion. Let DM_1, DM_2 and DM_3 be the set of three experts for choosing the best alternative under criterion. In this method, we used the two different weights of criteria which is based on the expert's opinion. By using this opinion, we evaluated the best alternative.

4.1 Algorithms

In this case, we discussed two types of algorithms in FMCDM problems. Firstly, explain the algorithm of fuzzy TOPSIS method. Here, all the data are represented in triangular fuzzy number using linguistics terms and take the one arbitrary weighted value for all criterion. Secondly, introduce the generalized FTOPSIS method using linguistics values for both alternative and criteria. In case of criteria, all the weighted values are determined by expert's opinion. By using two types of calculated weight, we determined the ranking order of alternative. The following methods of fuzzy TOPSIS and generalized fuzzy TOPSIS are described below.

Algorithm-1. (Fuzzy TOPSIS method)

Step 1. Construct a decision matrix $\Delta = (F_{ij})_{m \times n}$ using the set of alternatives under different criterion.

Step 2. Estimate the normalized value of decision-matrix $\widehat{F}_{\mathrm{ij}}$ in both benefit and cost criterion:

For benefit criterion,

$$\widehat{F}_{\mathrm{ij}} = \left(\frac{f_{1ij}}{f_{3j}^{+}}, \frac{f_{2ij}}{f_{3j}^{+}}, \frac{f_{3ij}}{f_{3j}^{+}}\right); \qquad where\ f_{3j}^{+} = max_i f_{3ij} \tag{4}$$

and in cost criteria

$$\widehat{F}_{\mathrm{ij}} = \left(\frac{f_{1j}^{-}}{f_{3ij}}, \frac{f_{1j}^{-}}{f_{2ij}}, \frac{f_{1j}^{-}}{f_{1ij}}\right); \qquad where\ f_{1j}^{-} = min_i f_{1ij} \tag{5}$$

Step 3. Compute the weighted value of normalized matrix by the relation:

$\widehat{H}_{\mathrm{ij}} = \widehat{F}_{ij}.\widehat{w}_{ij}$.

where, $\widehat{w}_{ij}$ is the weighted values of each alternative under different criterion.

Step 4. Compute FPIS ($\hat{A}^{+}$) and FNIS ($\hat{A}^{-}$) of each alternative as:

$$\hat{A}^{+}=\{\hat{H}_1^{+},\hat{H}_2^{+},\ldots,\hat{H}_n^{+}\}=\left\{\left(\max_j \hat{H}_{ij}\ |i\in B\right),\left(\min_j \hat{H}_{ij}\ |i\in C\right)\right\} \tag{6}$$

and $$\hat{A}^{-}=\{\hat{H}_1^{-},\hat{H}_2^{-},\ldots,\hat{H}_n^{-}\}=\left\{\left(\min_j \hat{H}_{ij}\ |i\in B\right),\left(\max_j \hat{H}_{ij}\ |i\in C\right)\right\} \tag{7}$$

where, B and C are the benefit and cost criterion**.**

Step 5. Regulate the separation fuzzy positive (D_i^{+}) and negative (D_i^{-}) distances of each alternative
$$d_i^{+}=\sum_{j=1}^{n} d(\hat{H}_{ij},\hat{H}_{ij}^{+}),\, i=1,2,\ldots m \tag{8}$$

and
$$d_i^{-}=\sum_{j=1}^{n} d(\hat{H}_{ij},\hat{H}_{ij}^{-}),\, i=1,2,\ldots m \tag{9}$$

where, $d(\hat{H}_{ij},\hat{H}_{ij}^{+})$ and $d(\hat{H}_{ij},\hat{H}_{ij}^{-})$ are the distance between two triangular fuzzy numbers using Equation (3).

Step 6. Finally construct the calculation of closeness coefficient and ranking order of each its alternatives. It can be defined as
$$CC_i=\frac{d_i^{-}}{d_i^{+}+d_i^{-}} \tag{10}$$

Using the procedure of closeness coefficients of each alternative, we have the decreasing order of its ranking alternative.

Algorithm-2. (Generalized fuzzy TOPSIS method)

Step 1. Construct a generalized fuzzy decision matrix $\Delta=(F_{ij})_{m\times n}$ using the linguistics terms in terms of criteria and alternative.

Step 2. Calculate the weighted values $\hat{w}_{ij}$ of each criterion under the linguistics data.

Step 3. Determine the normalized value of decision-matrix in both benefit and cost criterion.

For benefit criterion,
$$\hat{F}_{\mathrm{ij}}=\left(\frac{f_{1ij}}{f_{3j}^{+}},\frac{f_{2ij}}{f_{3j}^{+}},\frac{f_{3ij}}{f_{3j}^{+}}\right);\quad where\ f_{3j}^{+}=max_i f_{3ij} \tag{11}$$

and in cost criteria
$$\hat{F}_{\mathrm{ij}}=\left(\frac{f_{1j}^{-}}{f_{3ij}},\frac{f_{1j}^{-}}{f_{2ij}},\frac{f_{1j}^{-}}{f_{1ij}}\right);\quad where\ f_{1j}^{-}=min_i f_{1ij} \tag{12}$$

Step 4. Compute the weighted normalize matrix by the relation:
$$\hat{H}_{\mathrm{ij}}=\hat{F}_{ij}.\hat{w}_{ij}, \tag{13}$$

where, $\hat{w}_{ij}$ is the weighted values of each alternative.

Step 5. Calculate the generalized fuzzy positive $\hat{A}^{+}$ and negative $\hat{A}^{-}$ ideal solutions of each alternative.

These are determined as

$$\hat{A}^{+} = \{\hat{H}_1^{+}, \hat{H}_2^{+}, \dots, \hat{H}_n^{+}\} = \left\{\left(\max_j \hat{H}_{ij} \,|i \in B\right), \left(\min_j \hat{H}_{ij} \,|i \in C\right)\right\} \tag{14}$$

and
$$\hat{A}^{-} = \{\hat{H}_1^{-}, \hat{H}_2^{-}, \dots, \hat{H}_n^{-}\} = \left\{\left(\min_j \hat{H}_{ij} \,|i \in B\right), \left(\max_j \hat{H}_{ij} \,|i \in C\right)\right\} \tag{15}$$

where, B and C are the benefit and cost criterion.

Step 6. Calculate the generalized separation distances of each alternative:

$$d_i^{+} = \sum_{j=1}^{n} d(\hat{H}_{ij}, \hat{H}_{ij}^{+}), i = 1,2, \dots m \tag{16}$$

and

$$d_i^{-} = \sum_{j=1}^{n} d(\hat{H}_{ij}, \hat{H}_{ij}^{-}), i = 1,2, \dots m \tag{17}$$

where, $d(\hat{H}_{ij}, \hat{H}_{ij}^{+})$ and $d(\hat{H}_{ij}, \hat{H}_{ij}^{-})$ are the distance between two triangular fuzzy numbers using Equation (3).

Step 7. Lastly determine the closeness coefficient values of each its alternative:

$$CC_i = \frac{d_i^{-}}{d_i^{+} + d_i^{-}} \tag{18}$$

Step 8. Calculate the ranking order of each alternative for two different criteria weights under the basis of closeness values.

Step 9. Under the basis of average, then to compute the final closeness coefficient values of each alternative and its ranking order.

5. Food Processing Industry: A Case Study

In this section, we discuss the fuzzy MCDM approach to produce a straight forward case study in food processing industry in Odisha state, which is represented in triangular fuzzy numbers.

After China, India is the world's second-largest food producer, but it has the potential to overtake all others. Food and food items represent the largest consumption category in India, with a $181 billion market and expenditures on food accounting for approximately 21% of the country's GDP. It is projected that the domestic food market in India will reach $258 billion by 2015 and $344 billion by 2025, representing a growth of about 40% from the current market size (World of Food India). The agricultural basis is fairly solid, but there is relatively little food processing and a lot of waste.

In certain developed countries, food processing levels up to 80% are achieved, but in India, the overall processing level has lately dropped to 10%. Consequently, India's food processing industry is relatively tiny, and its portion of processed food exports to global trade has stayed at roughly 1.5%, or $3.2 billion. Regarding output, consumption, exports, and projected growth, the agro-food processing sector is one of the biggest in India, employing around 18% of the industrial labor force and ranking fifth. Numerous fruits, vegetables, and other food items ranging from temperate to tropical are also produced in India. In order to preserve and use fruits and vegetables to their full potential, food products must be processed. India offers great potential for the food processing business, which creates a vital connection between farmers and consumers, thanks to its diverse range of climatic zones, robust agricultural foundation, and rapid economic expansion.

This paper aims to investigate the current state and trends of India's food processing sector. Along with discussing the issues halting this sector's progress, the study also lists the limitations and issues encountered. The paper concludes with an analysis of prospects and some workable recommendations for the industry's ongoing development. An examination of the industry's strengths and weaknesses, as well as potential threats, is done while analyzing strengths and weaknesses. Strategies for expanding processed food product markets across the globe are also taken into consideration for the best food processing industry.

In this section, we used the fuzzy MCDM approach to produce a straight forward example in triangular fuzzy numbers. A potential investor might put money into a variety of food-processing companies in the Bhubaneswar city, such as Lite Bite Foods (A_1), PepsiCo (A_2), Cargill A_3), Cadbury(A_4), and Britannia (A_5) as these companies are prominent in the Indian food processing sector. These many food companies are portrayed as several alternatives. Choose the best option among these 5 options based on the many criteria. These are focuses on evaluating organizational performance from an employee-centric perspective within the food processing companies such as Skill development/ learning (C_1), Company culture (C_2), Job security (C_3), Work-life balance (C_4), and Salary and benefits (C_5). These criterion are directly influence workforce productivity, retention, and overall operational efficiency—key aspects that significantly impact the performance of food processing companies. All of these criteria are benefit criteria. In accordance with the linguistics concepts introduced in **Table 2** and **Table 3**, all criteria weights and alternative values are expressed as triangular fuzzy numbers. The evaluation was carried out by a panel of three experts from the food processing industry, selected for their extensive knowledge and experience. The panel included professionals with qualifications such as PhD in Food Technology, MTech in Food Engineering, and MBA in Operations Management. Their designations comprised Senior Food Technologist, Quality Manager, and Industry Consultant, with experience ranging from 8 to 20 years. **Table 4** presents the expert assessments using linguistic terms to construct the decision matrix, while **Tables 5** and **6** show the expert-derived fuzzy weights for the criteria. All these Tables are shown in below:

Table 2. Linguistic value of assessment gradings.

Linguistics values	TFN
Very poor (VP)	(0.00,0.35,0.45)
Poor(P)	(0.35,0.45,0.50)
Medium (M)	(0.45,0.60,0.65)
Good (G)	(0.60,0.75,0.80)
Very good (VG)	(0.75,0.85,0.92)
Excellent (E)	(0.90,1.00,1.00)

Table 3. Linguistic value of criteria weights.

Linguistics value	Weighted fuzzy data
Very important (VI)	(0.67,0.84,1.00)
Important(I)	(0.45,0.67,0.84)
Moderate(M)	(0.27,0.45,0.67)
Unimportant (U)	(0.15,0.27,0.45)
Very unimportant (VU)	(0.00,0.15,0.27)

Table 4. Experts' grading under the linguistics value.

Alternative	DM_1	DM_2	DM_3
A_1	E	VG	G
A_2	G	G	E
A_3	VG	E	M
A_4	M	VG	G
A_5	G	G	M
A_1	G	VG	M
A_2	VG	M	M
A_3	G	VG	VG
A_4	E	VG	E
A_5	M	M	M
A_1	M	E	VG
A_2	G	VG	G
A_3	M	VG	M
A_4	G	G	M
A_5	VG	M	VG
A_1	M	G	VG
A_2	G	VG	VG
A_3	G	G	G
A_4	E	VG	VG
A_5	E	G	VG
A_1	VG	G	G
A_2	M	M	VG
A_3	E	VG	G
A_4	VG	G	VG
A_5	G	G	M

Now to construct the fuzzy group decision matrix and its two distinct weighted values for each criterion by the help of **Tables 2-6**, which is detailed in **Table 7**. Then by Equations (13) and (14), the normalized values of decision matrix in both criteria are determined. **Table 8** shows the normalized fuzzy matrix. **Table 9** gives the first weighted normalized matrix with its positive, negative ideal solutions, DFPIS, DFNIS and its closeness coefficient values of each alternatives using Equations (15), (16) and (17). Similarly, **Table 10** lists the second weighted normalized values, as well as its positive and negative optimal solutions with its distance and closeness values. All these **Tables 8**, **9** and **10** are shown in the appendix. **Table 11** displays the final ranking order of alternatives by averaging two closeness values of each alternative. All the tabulated values are given below.

Table 5. Expert's grading under the first linguistics weights.

Criteria	DM_1	DM_2	DM_3
C_1	M	M	VI
C_2	I	M	VI
C_3	VI	I	M
C_4	VI	VI	I
C_5	I	I	M

Table 6. Expert's grading under the second linguistics weights.

Criteria	DM_1	DM_2	DM_3
C_1	M	I	VI
C_2	U	M	VI
C_3	I	U	M
C_4	M	M	I
C_5	VI	I	M

Table 7. Fuzzy decision matrix.

Alt./Crt.	C_1	C_2	C_3	C_4	C_5
A_1	(0.750,0.867,0.907)	(0.600,0.733,0.790)	(0.700,0.817,0.857)	(0.600,0.733,0.790)	(0.650,0.783,0.840)
A_2	(0.700,0.833,0.867)	(0.550,0.683,0.740)	(0.650,0.783,0.840)	(0.700,0.817,0.880)	(0.550,0.683,0.740)
A_3	(0.700,0.817,0.857)	(0.700,0.817,0.880)	(0.550,0.683,0.740)	(0.600,0.750,0.800)	(0.750,0.867,0.907)
A_4	(0.600,0.733,0.790)	(0.850,0.950,0.973)	(0.550,0.700,0.750)	(0.800,0.900,0.947)	(0.700,0.817,0.880)
A_5	(0.550,0.700,0.750)	(0.450,0.600,0.650)	(0.650,0.767,0.830)	(0.800,0.900,0.947)	(0.550,0.700,0.750)
w'_j	(0.403,0.580,0.780)	(0.463,0.653,0.837)	(0.463,0.653,0.837)	(0.597,0.783,0.947)	(0.390,0.597,0.783)
w''_j	(0.463,0.653,0.837)	(0.363,0.520,0.723)	(0.290,0.463,0.653)	(0.330,0.523,0.727)	(0.463,0.653,0.837)

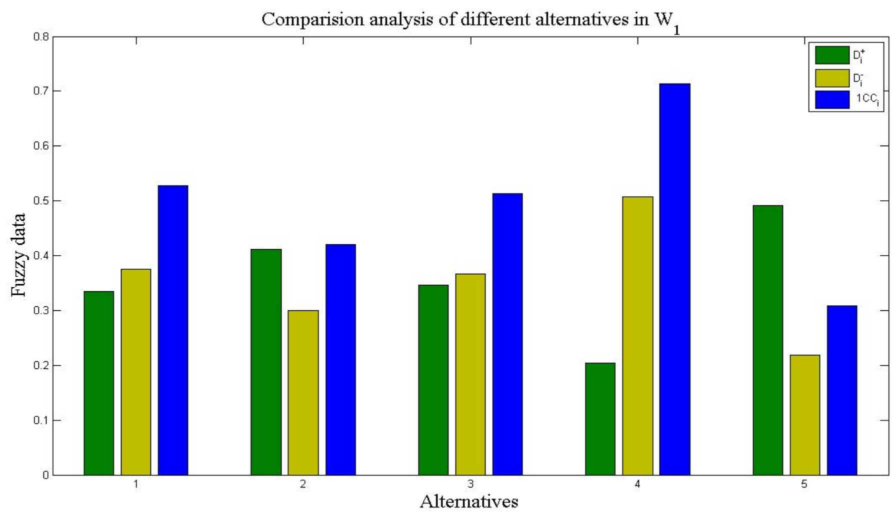

Figure 1. Histography of DFPIS, DFNIS, and closeness coefficients in different weights.

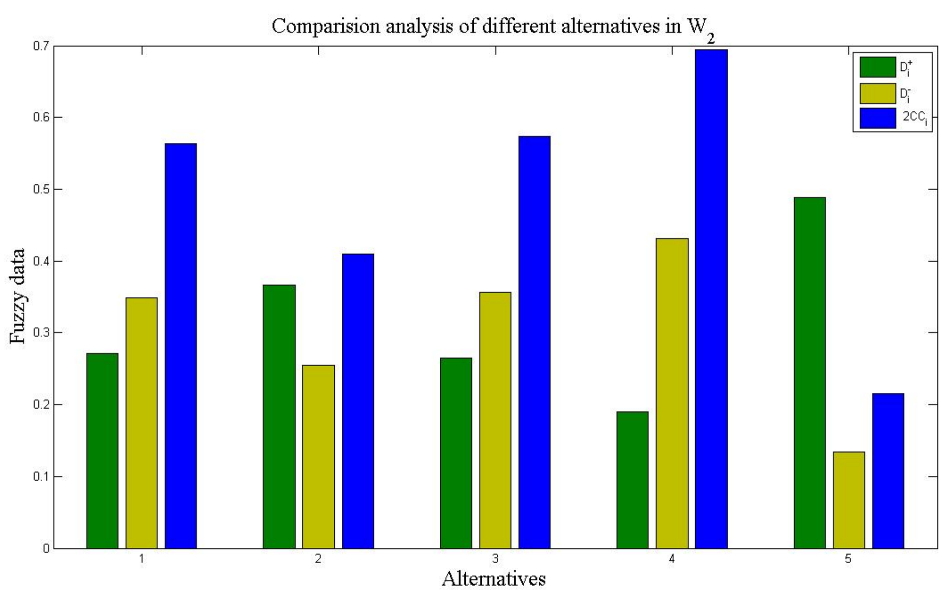

Figure 2. Histography of DFPIS, DFNIS, and Closeness Coefficients in second weight.

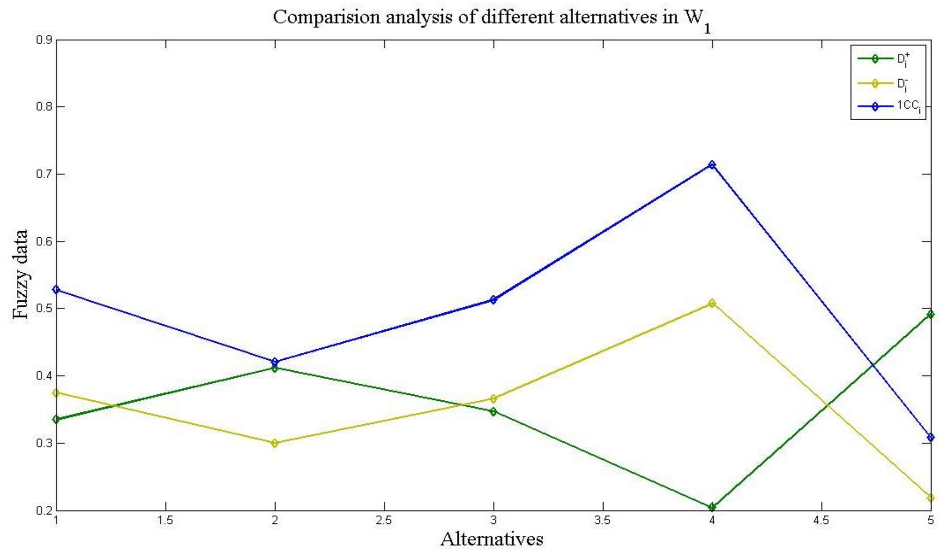

Figure 3. Line graph of DFPIS, DFNIS, and closeness coefficients in first weight.

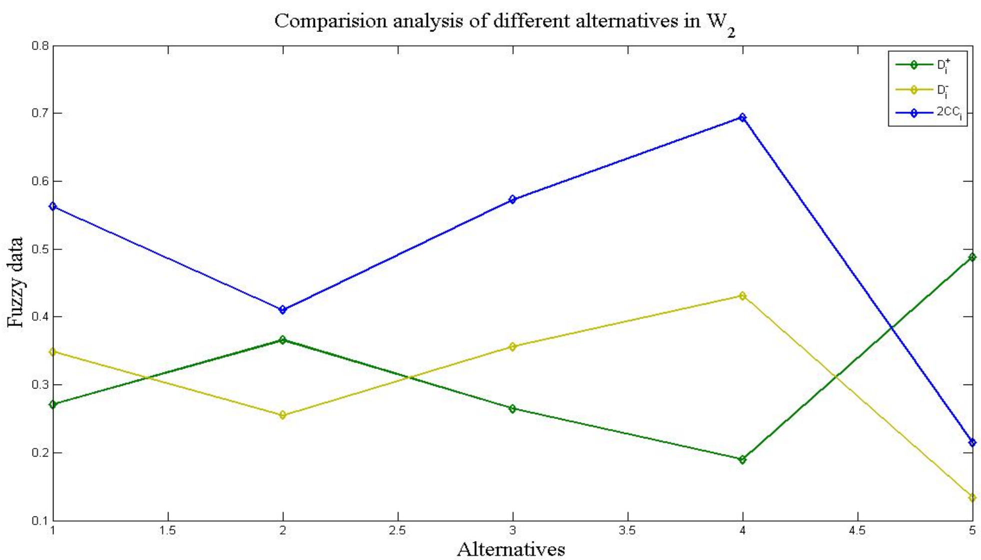

Figure 4. Line graph of DFPIS, DFNIS, and closeness coefficients in second weight.

Table 11. Closeness coefficients and ranking order of each alternative.

Alt.	$1CC_i$	$2CC_i$	CC_i	Rank
A_1	0.528	0.563	0.546	2
A_2	0.421	0.41	0.416	4
A_3	0.513	0.573	0.543	3
A_4	0.714	0.694	0.704	1
A_5	0.308	0.215	0.266	5

According to the table above, the integral performance index is ranked in the following order:
$$A_4 > A_1 > A_3 > A_2 > A_5.$$

Therefore, A_4 is a useful food processing company to invest the money in the problem. The graphical representation of the negative, positive, and overall performance indices is shown in **Figure 1**, **Figure 2**, **Figure 3** and **Figure 4**.

5.1 Fuzzy TOPSIS

In this subsection, we discussed a case study on food-processing companies in the Bhubaneswar city by FTOPSIS method. Now to construct the fuzzy aggregated decision matrix by the help of **Tables 2-6**, which is detailed in **Table 12**. Then by Equations (4) and (5), the normalized values of decision matrix in both criteria are determined. **Table 13** shows the normalized fuzzy matrix. **Table 14** gives the weighted normalized matrix with its positive, negative ideal solutions, DFPIS and DFNIS values of each alternatives using Equations (6), (7) and (8), which is shown in the appendix section. **Table 15** displays the final ranking order of alternatives by closeness values of each alternative. All the tabulated values are given below.

Table 12. Aggregated decision matrix.

Alt./Crt.	C_1	C_2	C_3	C_4	C_5
A_1	(0.75,0.87,0.90)	(0.6,0.73,0.79)	(0.7,0.81,0.85)	(0.6,0.73,0.79)	(0.65,0.78,0.84)
A_2	(0.7,0.833,0.87)	(0.55,0.68,0.74)	(0.65,0.78,0.84)	(0.7,0.81,0.88)	(0.55,0.68,0.74)
A_3	(0.7,0.81,0.85)	(0.7,0.81,0.76)	(0.55,0.68,0.74)	(0.6,0.75,0.8)	(0.75,0.86,0.90)
A_4	(0.65,0.77,0.83)	(0.85,0.9,0.97)	(0.55,0.7,0.75)	(0.8,0.9,0.94)	(0.7,0.81,0.88)
A_5	(0.55,0.7,0.75)	(0.45,0.6,0.65)	(0.65,0.77,0.83)	(0.75,0.86,0.90)	(0.55,0.7,0.75)

Table 15. Closeness coefficients and ranking order of each alternative.

Alt.	CC_i	Rank
A_1	0.602	2
A_2	0.387	4
A_3	0.436	3
A_4	0.787	1
A_5	0.285	5

The food processing case study emphasizes selecting the most suitable food processing company based on multiple benefit-related criteria such as Skill Development/Learning, Company Culture, Job Security, Work–Life Balance, and Salary and Benefits using the generalized fuzzy TOPSIS approach. However, the scope of the study is confined to a single state with a limited number of alternatives and decision makers. To improve the generalizability and applicability of the findings, the generalized FTOPSIS method may be expanded to additional case studies across various industrial sectors, regions, and decision-making environments. Such extended case studies would further validate the robustness, reliability, and practical relevance of the proposed approach.

6. Comparison Analysis with Other Methods

We discuss the FMCDM approach's applicability in this section. Next, the proposed method is compared with another FMCDM one. The Wang publication provides an example of how to evaluate the FMCDM problem based on positive and negative extreme solutions, and this approach is suggested as a follow-up.

All the tabulated data are discussed in the appendix (**Tables 16-20**). As a result of this study, we came to the conclusion that the ranking of alternatives goes $A_2 > A_1 > A_3$.

The steps in this process are as follows:

- Create a fuzzy decision-matrix utilizing various criteria and alternatives.
- The computation of a normalized fuzzy decision matrix.
- Next, compute the negative and positive extreme solutions using Min-Max procedures.
- Next, compute the strength and weakness matrices.
- We now need to calculate the weighted strength and weakness indexes.
- Next, determine the negative and positive indices.
- Next, compute overall performance indexes.
- To calculate the ranking of alternatives.

Table 21. Comparison analysis.

Methodology	**Order of the ranking**
Proposed methodology	$A_4 > A_1 > A_3 > A_2 > A_5$.
FTOPSIS	$A_4 > A_1 > A_3 > A_2 > A_5$.
Suggested methodology (Wang, 2011).	$A_2 > A_1 > A_3$.
Suggested methodology (Zafar, 2020).	$A_1 > A_2$

From **Table 17**, it is clear that all three methodologies evaluate the same set of alternatives but lead to different ranking orders. The proposed methodology yields a complete and clear ranking ($A_4 > A_1 > A_3 > A_2 > A_5$) and identifies A_4 as the most effective food-processing business for investment in both generalized fuzzy TOPSIS and FTOPSIS. The classical Fuzzy TOPSIS method evaluates alternatives using triangular fuzzy numbers derived from linguistic terms and typically relies on fixed or arbitrarily assigned criteria weights. While effective, it offers limited flexibility in capturing expert uncertainty. In contrast, the Generalized Fuzzy TOPSIS approach extends the classical method by incorporating linguistic values for both alternative ratings and criteria weights, where the weights are determined directly through expert judgment and fuzzy aggregation. In contrast, the method of Wang (2011) provides only a partial ranking ($A_2 > A_1 > A_3$), while the approach of Zulqarnain et al. (2020) results in a very limited ranking ($A_1 > A_2$), indicating lower discriminatory power. Although all three approaches are based on fuzzy TOPSIS principles using triangular fuzzy numbers, the proposed method is simpler and more informative because it produces closeness coefficient values in the range [0,1], allowing easy and transparent comparison among all alternatives. Moreover, unlike Wang (2011) and Zulqarnain et al. (2020), which rely on single-weight structures and are applied to different decision contexts, the proposed methodology incorporates multiple expert-based weighting schemes and averages the resulting closeness coefficients, thereby improving robustness and reducing individual expert bias. This results in a broader and more realistic modelling of uncertainty, producing more dispersed closeness values while still maintaining consistent rankings. Overall, the generalized method provides a more sensitive and robust assessment compared to the traditional Fuzzy TOPSIS. The proposed approach not only remains compatible with existing FMCDM methods but also offers greater completeness, simplicity, and practical relevance for investment decision-making in the food-processing industry.

7. Conclusion and Future Scope

Numerous decision-related real-world applications have been found for the FMCDM problem. In this study, a method for selecting the best food-processing alternative based on the different criterion under generalized fuzzy TOPSIS was developed. This paper also considers how each choice deviates from both the positive and negative ideal solutions under two different criteria, weights and determined two closeness coefficient values. After that, averaging the two closeness values, we found the better ranking order of alternative. The basis for the ranking order is the longer and smaller distances between alternatives to both positive and negative ideal solutions. In generalized fuzzy TOPSIS, several various techniques have been addressed.

Future studies can extend the proposed fuzzy TOPSIS approach using advanced fuzzy environments such as intuitionistic, interval-valued, or type-2 fuzzy sets to better handle uncertainty. The method can also be integrated with other MCDM techniques or optimization algorithms to enhance result accuracy. Additionally, applying this framework to various industrial sectors will help validate its effectiveness and practical relevance.

Appendix

Table 8. Normalized fuzzy decision matrix.

Alt./Crt.	C_1	C_2	C_3	C_4	C_5
A_1	(0.827,0.956,1.000)	(0.617,0.753,0.812)	(0.817,0.953,1.000)	(0.634,0.774,0.834)	(0.717,0.863,0.926)
A_2	(0.772,0.918,0.956)	(0.565,0.702,0.761)	(0.758,0.914,0.980)	(0.739,0.863,0.929)	(0.606,0.753,0.816)
A_3	(0.772,0.901,0.945)	(0.719,0.840,0.904)	(0.642,0.797,0.863)	(0.634,0.792,0.845)	(0.827,0.956,1.000)
A_4	(0.662,0.808,0.871)	(0.874,0.976,1.000)	(0.642,0.817,0.875)	(0.845,0.950,1.000)	(0.772,0.901,0.970)
A_5	(0.606,0.772,0.827)	(0.462,0.617,0.668)	(0.758,0.895,0.968)	(0.845,0.950,1.000)	(0.606,0.772,0.827)

Table 9. First weighted value with DFPIS, DFNIS, and closeness coefficient.

Alt./Crt.	W_1C_1	W_1C_2	W_1C_3	W_1C_4	W_1C_5	$d_i^{+'}$	$d_i^{-'}$	$1CC_i$
A_1	0.333,0.554,0.780)	(0.286,0.492,0.680)	(0.378,0.623,0.837)	(0.378,0.606,0.790)	(0.279,0.515,0.725)	0.335	0.375	0.528
A_2	(0.311,0.533,0.746)	(0.262,0.458,0.637)	(0.351,0.597,0.820)	(0.441,0.676,0.880)	(0.236,0.450,0.639)	0.412	0.300	0.421
A_3	(0.311,0.522,0.737)	(0.333,0.548,0.757)	(0.297,0.520,0.723)	(0.378,0.620,0.800)	(0.322,0.571,0.783)	0.347	0.366	0.513
A_4	(0.267,0.469,0.679)	(0.404,0.638,0.837)	(0.297,0.533,0.732)	(0.504,0.744,0.947)	(0.301,0.538,0.760)	0.204	0.508	0.714
A_5	(0.244,0.448,0.645)	(0.214,9.403,0.559)	(0.351,0.584,0.811)	(0.504,0.744,0.947)	(0.236,0.461,0.647)	0.492	0.219	0.308
A^+	(0.333,0.554,0.780)	(0.404,0.638,0.837)	(0.378,0.623,0.837)	(0.504,0.744,0.947)	(0.322,0.571,0.783)			
A^-	(0.244,0.448,0.645)	(0.214,0.403,0.559)	(0.297,0.520,0.723)	(0.378,0.606,0.790)	(0.236,0.450,0.639)			

Table 10. Second weighted value with DFPIS, DFNIS, and closeness coefficient.

Alt./Crt.	W_2C_1	W_2C_2	W_2C_3	W_2C_4	W_2C_5	$d_i^{+''}$	$d_i^{-''}$	$2CC_i$
A_1	(0.383,0.624,0.837)	(0.224,0.392,0.587)	(0.237,0.441,0.653)	(0.209,0.405,0.606)	(0.332,0.564,0.775)	0.271	0.349	0.563
A_2	(0.357,0.600,0.800)	(0.205,0.365,0.550)	(0.220,0.423,0.640)	(0.244,0.451,0.676)	(0.281,0.492,0.683)	0.366	0.255	0.410
A_3	(0.357,0.588,0.791)	(0.261,0.437,0.654)	(0.186,0.369,0.564)	(0.209,0.414,0.614)	(0.383,0.624,0.837)	0.265	0.356	0.573
A_4	(0.306,0.528,0.729)	(0.317,0.508,0.723)	(0.186,0.378,0.571)	(0.279,0.497,0.727)	(0.357,0.588,0.812)	0.190	0.431	0.694
A_5	(0.281,0.504,0.692)	(0.168,0.321,0.483)	(0.220,0.414,0.632)	(0.261,0.479,0.696)	(0.281,0.504,0.692)	0.488	0.134	0.215
A^+	(0.383,0.624,0.837)	(0.317,0.508,0.723)	(0.237,0.441,0.653)	(0.279,0.497,0.727)	(0.383,0.624,0.837)			
A^-	(0.281,0.504,0.692)	(0.168,0.321,0.483)	(0.186,0.369,0.564)	(0.209,0.405,0.606)	(0.281,0.492,0.683)			

Table 13. Normalized value of decision-matrix.

Alt./Crt.	C_1	C_2	C_3	C_4	C_5
A_1	(0.827,0.955,1)	(0.616,0.753,0.811)	(0.817,0.953,1)	(0.75,0.774,0.834)	(0.866,0.863,0.926)
A_2	(0.772,0.919, 0.955)	(0.565,0.702,0.760)	(0.758,0.914,0.980)	(0.739,0.862,0.929)	(0.606,0.753,0.816)
A_3	(0.772,0.900,0.944)	(0.719,0.839,0.784)	(0.642,0.797,0.863)	(0.633,0.792,0.845	0.827,0.955,1)
A_4	(0.716,0.845,0.915)	(0.873,0.976,1)	(0.642,0.817,0.875)	(0.845,0.950,1)	(0.772,0.900,0.970)
A_5	(0.606,0.772,0.827)	(0.462,0.631,0.667)	(0.758,0.894,0.968)	(0.792,0.915,0.957)	(0.606,0.772,0.827)
Weight	0.25	0.2	0.2	0.2	0.15

Table 14. Weighted value of normalized matrix with DFPIS & DNIS.

Alt./Crt.	C_1	C_2	C_3	C_4	C_5	d_i^+	d_i^-
A_1	(0.206,0.238,0.25)	(0.123,0.150,0.162)	(0.163,0.190,0.2)	(0.15,0.154,0.166)	(0.13,0.129,0.138)	0.0855	0.129
A_2	(0.193,0.229,0.238)	(0.113,0.140,0.152)	(0.151,0.182,0.196)	(0.147,0.172,0.185)	(0.090,0.113,0.122)	0.123	0.077
A_3	(0.193,0.225,0.236)	(0.143,0.167,0.156)	(0.128,0.159,0.172)	(0.126,0.158,0.169)	0.124,0.143,0.15)	0.114	0.089
A_4	(0.179,0.211,0.228)	(0.174,0.195,0.2)	(0.128,0.163,0.175)	(0.169,0.190,0.2)	(0.115,0.135,0.145)	0.062	0.231
A_5	(0.151,0.193,0.206)	(0.092,0.126,0.133)	(0.151,0.178,0.193)	(0.158,0.183,0.191)	(0.090,0.115,0.124)	0.169	0.0676

Table 16. Decision matrix and its weighted values.

Alt./Crt.	C_1	C_2	C_3	C_4	C_5	C_6
A_1	(6.00,7.500, 9.000)	(6.750,8.50, 9.50)	(4.75,5.750,7.50)	(7.00,9.000, 10.00)	(6.250,8.000, 9.500)	(9.000,9.000, 9.000)
A_2	(6.500,8.50, 10.00)	(4.250,5.25, 6.50)	(7.50,9.50,10.00)	(5.750,7.500, 9.500)	(6.000,7.500, 9.000)	(4.500,4.500, 4.500)
A_3	(4.500,5.500, 7.00)	(7.50,9.50, 10.00)	(5.250,6.50,8.50)	(6.00,7.500, 9.000)	(6.500,8.500, 10.000)	(9.000,9.000, 9.000)
w_j	(0.50,0.725, 0.925)	(0.40,0.60, 0.850)	(0.5,0.725,0.925)	(0.275,0.500, 0.725)	(0.400,0.600, 0.850)	(0.400,0.600, 0.850)

Table 17. The normalization, negative and positive values.

Alt./Crt.	C_1	C_2	C_3	C_4	C_5	C_6
A_1	(0.600,0.750,0.900)	(0.675,0.850,0.950)	(0.475,0.575,0.750)	(0.700,0.900,1.000)	(0.625,0.800,0.950)	(0.500,0.500,0.500)
A_2	(0.650,0.850,1.000)	(0.450,0.525,0.650)	(0.750,0.950,1.000)	(0.575,0.750,0.950)	(0.600,0.750,0.900)	(1.000,1.000,1.000)
A_3	(0.450,0.550,0.700)	(0.750,0.950,1.000)	(0.525,0.650,0.850)	(0.600,0.750,0.900)	(0.650,0.850,1.000)	(0.500,0.500,0.500)
A^-	(0.450,0.550,0.700)	(0.450,0.525,0.650)	(0.475,0.575,0.750)	(0.575,0.750,0.950)	(0.600,0.750,0.900)	(0.500,0.500,0.500)
A^+	(0.650,0.850,1.000)	(0.750,0.950,1.000)	(0.750,0.950,1.000)	(0.700,0.900,1.000)	(0.650,0.850,1.000)	(1.000,1.000,1.000)

Table 18. Strength matrix and its weighted values.

Alt./Crt.	C_1	C_2	C_3	C_4	C_5	C_6	${W_i}^-$
A_1	0.375	0.588	0.000	0.263	0.088	0.000	(0.530,0.808,1.111)
A_2	0.550	0.000	0.638	0.025	0.000	1.000	(1.001,1.473,1.967)
A_3 N_gW^- N_gW^+	0.000	0.750	0.150	0.013	0.175	0.000	(0.448,0.670,0.934) (0.448,0.670,0.934) (1.001,1.473,1.967)

Table 19. The weakness matrix and its weighted values.

Alt./Crt.	C_1	C_2	C_3	C_4	C_5	C_6	${W_i}^+$
A_1	0.175	0.163	0.638	0.000	0.088	1.000	(0.906,1.339,1.814)
A_2	0.000	0.750	0.000	0.238	0.175	0.000	(0.435,0.674,0.958)
A_3	0.550	0.000	0.488	0.250	0.000	1.000	(0.988,1.477,1.991)
P_gW^-							(0.435,0.674,0.958)
P_sW^+							(0.988,1.477,1.991)

Table 20. The positive, negative and total performance indic.

Alt.	Negative indices (A^-)	Positive indices (A^+)	Total indices (A^*)	Rank
A_1	0.833	0.167	0.028	2
A_2	0.000	1.000	1.000	1
A_3	1.000	0.000	0.000	3

Conflicts of Interest
The authors declare that, we don't have any kind of conflict. The entire work has been carried by our own interest and mutual understanding with equal contribution.

Acknowledgments
The authors thank the editor and anonymous reviewers for their valuable comments, which improved the quality of this work. The authors declare that there is no funding. The data used during this study appear in the submitted manuscript.

AI Disclosure
During the preparation of this work the author(s) used generative AI in order to improve the language of the article. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

References

Baral S.P., Parida P.K., & Sahoo D. (2025). An enhanced TOPSIS-based framework for MCDM with uncertain weights: application to e-waste recycling partner selection. *Results in Control and Optimization*, *19*, 100545.

Baral, S.P., Parida, P.K., Sahoo, D., & Sahoo, S.K. (2023). A TOPSIS technique for multi-attribute group decision-making in fuzzy environment. *In International Conference on Advanced Communications and Machine Intelligence* (pp. 135-147). Springer Nature, Singapore.

Bellman, R.E., & Zadeh, L.A. (1970). Decision-making in a fuzzy environment. *Management Science*, *17*(4), B-141.

Bouhentala, M., Ghanai, M., & Chafaa, K. (2023). Interval-valued fuzzy estimation and its application to adaptive control of quadrotor. *Results in Control and Optimization*, *13*, 100337.

Capuano, N., Chiclana, F., Fujita, H., Herrera-Viedma, E., & Loia, V. (2017). Fuzzy group decision making with incomplete information guided by social influence. *IEEE Transactions on Fuzzy Systems*, *26*(3), 1704-1718.

Chang, D.Y. (1996). Applications of the extent analysis method on fuzzy AHP. *European Journal of Operational Research*, *95*(3), 649-655. https://doi.org/10.1016/0377-2217(95)00300-2.

Chen, S.J., & Hwang, C.L. (1992). Fuzzy multiple attribute decision making methods. *Fuzzy Multiple Attribute Decision Making: Methods and Applications* (pp. 289-486). Springer, Berlin, Heidelberg.

Coelho, L.M.G., Lange, L.C., & Coelho, H.M. (2017). Multi-criteria decision making to support waste management: A critical review of current practices and methods. *Waste Management & Research*, *35*(1), 3-28.

Duan, Y., Khokhar, M., Raza, A., Sharma, A., & Islam, T. (2025). The role of digital technology and environmental sustainability in circular supply chains based on the fuzzy TOPSIS model. *Environment, Development and Sustainability*, *27*(1), 1-32. https://doi.org/10.1007/s10668-024-05924-4.

Dutta, P., & Borah, G. (2023). Multicriteria decision making approach using an efficient novel similarity measure for generalized trapezoidal fuzzy numbers. *Journal of Ambient Intelligence and Humanized Computing*, *14*(3), 1507-1529. https://doi.org/10.1007/s12652-021-03347-x.

Dwivedi, G., Srivastava, R.K., & Srivastava, S.K. (2018). A generalised fuzzy TOPSIS with improved closeness coefficient. *Expert Systems with Applications*, *96*, 185-195. https://doi.org/10.1016/j.eswa.2017.11.051.

Fan, Z.P., & Liu, Y. (2010). A method for group decision-making based on multi-granularity uncertain linguistic information. *Expert Systems with Applications*, *37*(5), 4000-4008. https://doi.org/10.1016/j.eswa.2009.11.016.

Ghosh, M., Guha, R., Singh, P.K., Bhateja, V., & Sarkar, R. (2019). A histogram based fuzzy ensemble technique for feature selection. *Evolutionary Intelligence*, *12*(4), 713-724. https://doi.org/10.1007/s12065-019-00279-6.

Han, F., Alkhawaji, R.N., & Shafieezadeh, M.M. (2025). Evaluating sustainable water management strategies using TOPSIS and fuzzy TOPSIS methods. *Applied Water Science*, *15*(1), 1-13. https://doi.org/10.1007/s13201-024-02336-7.

Hwang, C.L., & Yoon, K. (2012). *Multiple attribute decision making: methods and applications a state-of-the-art survey* (Vol. 186). Springer Science & Business Media. https://doi.org/10.1007/978-3-642-48318-93.

Jahanshahloo, G.R., Lotfi, F.H., & Izadikhah, M. (2006). Extension of the TOPSIS method for decision-making problems with fuzzy data. *Applied Mathematics and Computation*, *181*(2), 1544-1551.

Liu, Y., Gao, C., Ji, X., Zhang, Z., Zhang, Y., Liu, C., & Wang, Z. (2022). Simulation of water resources carrying capacity of the Hangbu River Basin based on system dynamics model and TOPSIS method. *Frontiers in Environmental Science*, *10*,1045907. https://doi.org/10.3389/fenvs.2022.1045907.

Mansour, I.B., Alaya, I., & Tagina, M. (2019). A gradual weight-based ant colony approach for solving the multiobjective multidimensional knapsack problem. *Evolutionary Intelligence*, *12*(2), 253-272.

Paramanik, R., Mahato, S.K., Kumar, N., Bhattacharyee, N., & Gupta, R.K. (2022). Optimization of system reliability for multi-level RAPs in intuitionistic fuzzy atmosphere using genetic algorithm. *Results in Control and Optimization*, *9*, 100175. https://doi.org/10.1016/j.rico.2022.100175.

Parida, P.K., & Sahoo, S.K. (2013). Multiple attributes decision making approach by TOPSIS technique. *International Journal of Engineering Research & Technology*, *2*(11), 907-912.

Parida, P.K., Baral, S.P., & Sahoo, S.K. (2021). TOPSIS method for multi-criteria decision making in fuzzy environment. *International Journal of Electrical Engineering & Technology*, *12*(11), 122-130.

Pei, Z. (2015). A note on the TOPSIS method in MADM problems with linguistic evaluations. *Applied Soft Computing*, *36*, 24-35. https://doi.org/10.1016/j.asoc.2015.06.042.

Piasecki, K., Roszkowska, E., & Łyczkowska-Hanćkowiak, A. (2019). Simple additive weighting method equipped with fuzzy ranking of evaluated alternatives. *Symmetry*, *11*(4), 482. https://doi.org/10.3390/sym11040482.

Prakash, K.A., & Suresh, M. (2024). Multi-criteria decision making in linguistic values of neutrosophic trapezoidal fuzzy multi-numbers. *Evolutionary Intelligence*, *17*(1), 349-360. https://doi.org/10.1007/s12065-023-00814-6.

Raut, U., & Mishra, S. (2021). A new Pareto multi-objective sine cosine algorithm for performance enhancement of radial distribution network by optimal allocation of distributed generators. *Evolutionary Intelligence*, *14*(4), 1635-1656. https://doi.org/10.1007/s12065-020-00428-2.

Revathi, M., & Valliathal, M. (2023). Website selection for online shopping by multi-criteria decision analysis using symmetric hendecagonal fuzzy number. *International Journal of Mathematics in Operational Research*, *24*(3), 339-359. https://doi.org/10.1504/IJMOR.2023.129485.

Saeli, M., Micale, R., Seabra, M.P., Labrincha, J.A., & La Scalia, G. (2020). Selection of novel geopolymeric mortars for sustainable construction applications using fuzzy TOPSIS approach. *Sustainability*, *12*(15), 5987.

Sahoo, D., Parida, P.K., & Pati, B. (2024). Efficient fuzzy multi-criteria decision-making for optimal college location selection: A comparative study of min–max fuzzy TOPSIS approach. *Results in Control and Optimization*, *15*, 100422. https://doi.org/10.1016/j.rico.2024.100422.

Sahoo, D., Parida, P.K., Baral, S.P., & Pati, B. (2025). An innovative aggregation operator for enhanced decision-making: a study on interval-valued Pythagorean fuzzy soft sets in material selection. *Applied Soft Computing*, *172*, 112888. https://doi.org/10.1016/j.asoc.2025.112888.

Sahoo, D., Parida, P.K., Baral, S.P., & Sahoo, S.K. (2023). A generalized fuzzy TOPSIS technique in multi-criteria decision-making for evaluation of temperature. *International Conference on Advanced Communications and Machine Intelligence* (pp. 71-81). Springer Nature, Singapore. https://doi.org/10.1007/978-981-99-2768-5_7.

Saikia, R., Garg, H., & Dutta, P. (2020). Fuzzy multi-criteria decision-making algorithm under intuitionistic hesitant fuzzy set with novel distance measure. *International Journal of Mathematical, Engineering and Management Sciences*, *5*(3), 473. https://doi.org/10.33889/IJMEMS.2020.5.3.039.

Sharma, J., & Tripathy, B.B. (2023). An integrated QFD and fuzzy TOPSIS approach for supplier evaluation and selection. *The TQM Journal*, *35*(8), 2387-2412. https://doi.org/10.1108/TQM-09-2022-0295.

Tan, Y.T., Shen, L.Y., Langston, C., & Liu, Y. (2010). Construction project selection using fuzzy TOPSIS approach. *Journal of Modelling in Management*, *5*(3), 302-315. https://doi.org/10.1108/17465661011092669.

Tomasiello, S., & Alijani, Z. (2021). Fuzzy-based approaches for agri-food supply chains: a mini-review. *Soft Computing*, *25*(11), 7479-7492. https://doi.org/10.1007/s00500-021-05707-3.

Triantaphyllou, E., & Lin, C.T. (1996). Development and evaluation of five fuzzy multiattribute decision-making methods. *International Journal of Approximate Reasoning, 14*(4), 281-310.

Wang, J., Liu, S.Y., & Zhang, J. (2005). An extension of TOPSIS for fuzzy MCDM based on vague set theory. *Journal of Systems Science and Systems Engineering*, *14*, 73-84. https://doi.org/10.1007/s11518-006-0182-y.

Wang, Y.J. (2011). Fuzzy multi-criteria decision-making based on positive and negative extreme solutions. *Applied Mathematical Modelling*, *35*(4), 1994-2004. https://doi.org/10.1016/j.apm.2010.11.011.

Wang, Y.J., & Lee, H.S. (2007). Generalizing TOPSIS for fuzzy multiple-criteria group decision-making. *Computers & Mathematics with Applications*, *53*(11), 1762-1772. https://doi.org/10.1016/j.camwa.2006.08.037.

Wang, Z.C., Ran, Y., Chen, Y., Yang, X., & Zhang, G. (2022). Group risk assessment in failure mode and effects analysis using a hybrid probabilistic hesitant fuzzy linguistic MCDM method. *Expert Systems with Applications*, *188*, 116013. https://doi.org/10.1016/j.eswa.2021.116013.

Xuan, H., Liu, Q., Wang, L., & Yang, L. (2022). Decision-making on the selection of clean energy technology for green ships based on the rough set and TOPSIS method. *Journal of Marine Science and Engineering*, *10*(5), 579.

Xue, X., Poonia, M., Abdulsahib, G.M., Bajaj, R.K., Khalaf, O.I., Dhumras, H., & Shukla, V. (2023). On cohesive fuzzy sets, operations and properties with applications in electromagnetic signals and solar activities. *Symmetry*, *15*(3), 595. https://doi.org/10.3390/sym15030595.

Yazdi, A.K., Hanne, T., & Gómez, J.C.O. (2020). Evaluating the performance of Colombian banks by hybrid multicriteria decision making methods. *Journal of Business Economics and Management*, *21*(6), 1707-1730.

Yazdi, A.K., Spulbar, C., Hanne, T., & Birau, R. (2022a). Ranking performance indicators related to banking by using hybrid multicriteria methods in an uncertain environment: a case study for Iran under COVID-19 conditions. *Systems Science & Control Engineering*, *10*(1), 166-180. https://doi.org/10.1080/21642583.2022.2052996.

Yazdi, A.K., Wanke, P.F., Hanne, T., Abdi, F., & Sarfaraz, A.H. (2022b). Supplier selection in the oil & gas industry: A comprehensive approach for multi-criteria decision analysis. *Socio-Economic Planning Sciences*, *79*, 101142.

Zadeh, L.A. (1965). Fuzzy sets. *Information and Control*, *8*(3), 338-353.

Zimmermann, H.J. (1987). *Fuzzy set, decision making, and expert systems*. Kluwer Academic Publishing, Boston.

Zouggari, A., & Benyoucef, L. (2012). Simulation based fuzzy TOPSIS approach for group multi-criteria supplier selection problem. *Engineering Applications of Artificial Intelligence*, *25*(3), 507-519.

Zulqarnaın, R.M., Saeed, M., Ali, B., Abdal, S., Saqlaın, M., Ahamad, M.I., & Zafar, Z. (2020). Generalized fuzzy TOPSIS to solve multi-criteria decision-making problems. *Journal of New Theory*, *2020*(32), 40-50.