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MultiFuzzTOPS: A Fuzzy Multi-Criteria Decision-Making Model Using Type-2 Soft Sets and TOPSIS

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Abstract: Effective and optimal decision-making can enhance system performance, potentially leading to a positive reputation and financial gains. Multi-criteria decision-making (MCDM) is an important research topic widely applied to practical decision-making problems. Using the basic idea of symmetry to balance the arrangement where elements or features have an equality or similarity in distribution, MCDM provides robust decisions in such multi-dimensional complex issues. This study proposes MultiFuzzTOPS, a decision-making model to deal with complexity of multi-criteria decision-making. The proposed MultiFuzzTOPS leverages the fuzzy logic and soft sets such as type-2 soft sets (T2SS) and technique for order preference by similarity to ideal solution (TOPSIS) for decision-making. We validate the proposed model by implementing it to solve the pesticide selection problem in food science by considering various criteria for the selection of pesticides. Our proposed MultiFuzzTOPS recommends the best pesticide compared with its counterparts because it covers the maximum information for the selection of the best alternative. Results are ranked on the basis of the Hamming distance and similarity coefficient. We also validate the effectiveness by performing the sensitivity analysis, and the validation shows the reliability and effectiveness of our proposed model.

Keywords: fuzzy multi-criteria decision-making (FMCDM); integrated pest management (IPM); symmetry; type-2 soft sets (T2SS); technique for order preference by similarity to ideal solution (TOPSIS)

1. Introduction

Decision-making is the process of identifying and addressing the problem of a group of people who intend to fulfill the goal of the decision problem more satisfactorily than others [1–3]. In various scientific disciplines, such as the social sciences, medical sciences, and engineering, there are numerous decision problems [4–6]. Various factors play a role in decision-making that make it extremely difficult. Using the basic idea of symmetry to balance the arrangement where elements or features have an equality or similarity in

distribution, multi-criteria decision-making (MCDM) provides robust decisions in these complex issues where selecting the best alternative is extremely difficult [7,8]. Symmetry in the MCDM ensures consistency and fairness by balancing the weighting or preference of the individual criteria. This fair treatment facilitates transparent decision-making processes and prevents bias.

Symmetry promotes rational decision-making by enabling the fair comparison of alternatives across a variety of criteria [9–11]. Decision makers can efficiently evaluate and compare options in a variety of applications, including project selection, efficient planning and resource allocation, by incorporating symmetry into MCDM frameworks [12,13]. MCDM plays an important role in life, such as transportation, investment, defense, engineering, biology, economics, agriculture, medicine, environmental science, etc. [14,15]. MCDM is a transparent and structured methodology that allows rational discrimination between different options based on a set of criteria against which each option is evaluated. However, in the real world, there is an element of vagueness and uncertainty in the implementation of MCDM. The symmetric and asymmetric perspectives in Type II soft sets involve studying how the parameters and elements interact in a balanced manner, emphasizing the equality of importance between the two aspects. This symmetry helps in analyzing the relationships and decision-making processes based on Type II soft sets in a more balanced and equitable way. Imprecise or uncertain information provides a more nuanced way to analyze and process data.

One of the important aspects that needs effective decision-making is pesticide selection in the agriculture domain. Agriculture is the backbone of human survival on Earth, providing vital commodities such as food, fiber, oxygen, and wood. The use of pesticides in agriculture is inevitable to maintain high product quality and reduce yield losses. However, their handling and use is not always optimal and does not always comply with manufacturers' specifications. This is often the case in practice and poses a major problem for farmers in deciding which pesticide is best.

In developing countries, pesticides are currently a widely used tool for pest and disease control. However, practice and the literature indicate that some pesticides are not as effective, and there is a widespread perception that the intensive use of pesticides leads to vulnerable farming systems [16–19]. Integrated pest management (IPM) is an important way to limit the negative impacts of pesticides. The guiding principle of IPM is to sustainably reduce the number of pesticides used in highly managed cropping systems [20]. Failure to include actionable information on pesticide impacts is due to improper pesticide selection. Rather than focusing on regulating the use of pesticides in agriculture, as has been done in the past, we must instead prioritize education and market-based solutions for this problem. Intelligent, science-based evaluation of pesticides is needed to allow for accurate comparisons between pesticide products. The objective of this study is to conduct a comprehensive analysis of pesticides with the help of experts to develop a decision-making guide. It also aims to analyze the group performance of the multiplicative algorithm to filter out the best solution.

In this study, a fuzzy MultiFuzzy TOPS model that employs MCDM is proposed to overcome the problems of vagueness and uncertainty in the real world. MCDM algorithms are widely used in the development of intelligent decision support systems (IDSSs) for accurate decision-making. In many disciplines, modern fuzzy set theory methods exist to deal with uncertainty. The applicability and robustness of such systems to solve complex real-world problems with fuzzy data has been demonstrated in the literature. Undoubtedly, fuzzy set theory has many applications in the real world. Although a real-world case study in agriculture is considered in this study, the proposed algorithm can be applied to a wide range of other decision problems. Besides this, the theory of type-2 soft sets (T2SS) has been presented for the first time by Chatterjee et al. [21]. The idea of type-2 soft sets is comprehensive and more influential tool in parameterized information depiction. This has prospective application in multiple areas; policy making, clinical diagnosis, financial

analysis, capital evaluation, health science, textural classification, and problem solving are just a few examples. The main contributions of this study are listed below:

- Propose a novel fuzzy decision-making model MultiFuzzTOPS that employs multi-criteria decision-making, fuzzy logic, and soft sets such as type-2 soft sets (T2SS) and technique for order preference by similarity to ideal solution (TOPSIS).
- Optimize the proposed model to increase its accuracy by employing the normalized Hamming distance.
- Implement the proposed model and solve the pesticide selection problem in agriculture and food science.
- Validate the proposed model by comparative analysis.

The rest of the paper is organized as follows. Section 2 provides the preliminaries and a literature review on decision-making using MCDM, fuzzy set theory, and soft set theory algorithms to identify the research gaps. Section 3 presents the proposed MultiFuzzTOPS using type-2 soft sets (T2SS) with technique for order preference by similarity to ideal solution (TOPSIS). Numerical computations and implementation details of the proposed MultiFuzzTOPS model are presented in Section 4. The accuracy of our proposed model is validated by sensitivity and comparative analysis in Section 5. The real-life applicability and limitations of our study are presented in Section 6. Finally, a comprehensive conclusion and future directions are given in Section 7.

2. Preliminaries and Literature Review

Considering novice readers and experts of the domain, we have divided this section into preliminaries and a state-of-the-art literature review.

2.1. Preliminaries

This subsection describes some relevant basic definitions such as the TOPSIS method, soft sets, and type-2 soft sets, especially for inexperienced readers.

2.1.1. TOPSIS Method

Hwang et al. defined in [22] that the TOPSIS algorithm allows alternatives to be ranked in order to solve numerous decision problems. The decision maker separates the criteria into evaluation factors. Using the Euclidean distance formula, the algorithm searches for the optimal option with the smallest distance from the positive ideal solution (PIS) and the largest distance from the negative ideal solution (NIS). With a positive ideal solution, the utility criteria are maximized, while the cost requirements are reduced. A collection of alternatives is evaluated and ranked in ascending order of closeness to the ideal solution.

2.1.2. Soft Sets

According to Molodtsov [23], a pair (F, E) is called a soft set over U if and only if F is a mapping of E into the set of all subsets of the set U , i.e., $F : E \rightarrow P(U)$, where $P(U)$ the power set of U and E is a set of parameters. The soft set is a parameterized family of subsets of the set U . Every set $F(e), e \in E$ from this family may be considered the set of the element of the soft set (F, E) or as the $\in$ -element of the soft set. The above concept is illustrated by the following example.

Example 1. In [23], Molodtsov discussed that U is a set of shoes under consideration, A is the set of parameters, each parameter being a word, a phrase or sentences. Soft sets (F, E) describe the attractive shoes which Mr. Ali wants to buy. Suppose there are five shoes in the universe, given by $U = \{\text{Set of Shoes}\} = \{y_1, y_2, y_3, y_4, y_5\}$ and the set of attributes given by $A = \{\text{Color, Comfortable, Cheap, durable}\} = \{e_1, e_2, e_3, e_4\}$. Let $E = \{e_1, e_2\} = \{\text{Color, comfortable}\}$ be those attributes that Mr. Ali is interested in when buying shoes. Let $E \subset A$ and suppose the following:

$F : E \rightarrow P(U)$, given by;

$$F(e_1) = F(\text{colour}) = \{y_1, y_2\},$$

$$F(e_2) = F(\text{comfortable}) = \{y_1, y_2, y_3\},$$

We can view the soft sets (F, E) as the collection of the following approximation:

$$(F, E) = \{(\text{colour}, \{y_1, y_2\}), (\text{comfortable}, \{y_1, y_2, y_3\})\}.$$

2.1.3. Type-2 Soft Sets (T2SS)

According to Chatterjee et al. [21], let (P, Q) be a soft universe and $S(P)$ be the group of all type-1 soft set over (P, Q) . Then, a mapping $F : A \rightarrow S(P)$, $A \in Q$ is called a type-2 soft set over (P, Q) and it is denoted by $[G, A]$. In this case, corresponding to each parameter $e \in A$, $F(e)$ is a type-2 soft set. Thus, for each $e \in A$, there exists a type-1 soft set (F_e, R_e) such that $F(e) = (F_e, R_e)$. The above concept is illustrated by the following example.

Example 2. In [21] Chatterjee et al., presented that U is a set of shoes under consideration, and A is the set of parameters, each parameter being a word, a phrase, or a sentence. Soft sets (F, E) describe the attractiveness of the shoes that Mr. Ali wants to buy. Suppose there are five shoes in the universe, given by

$$U = \{\text{Set of Shoes}\} = \{y_1, y_2, y_3, y_4, y_5\}$$

And the set of attributes is given by $A = \{\text{Color, Comfortable, Cheap, durable}\} = \{e_1, e_2, e_3, e_4\}$

Let $E = \{e_2, e_3\} = \{\text{Comfortable, cheap}\}$ our primary set of parameters.

Then, $E \subset A$.

Let $[F, E]$ be a type-2 soft set over U , which denotes the attributes of the above-mentioned shoes. Suppose $F : E \rightarrow S(X)$ is defined as follows:

$$F(\text{comfortable}) = \left\{ \frac{\text{very comfortable}}{y_1, y_2}, \frac{\text{low comfortable}}{y_3, y_4} \right\}$$

$$F(\text{cheap}) = \left\{ \frac{\text{very cheap}}{y_1, y_5}, \frac{\text{low cheap}}{y_2, y_3} \right\}.$$

The above-mentioned type-2 soft sets are interpreted, as out of the various shoes, y_1 and y_2 are very comfortable and y_3 and y_4 are less comfortable. y_1 and y_5 are very cheap and y_2 and y_3 are less cheap. Here, the set of parameters E constitutes the set of primary parameters, whereas the set $\{\text{very cheap, very comfortable, low cheap, low comfortable}\}$ is the set of underlying parameters. On the basis of these definitions, we have proposed an algorithm based on type-2 soft sets and multi-criteria decision-making problems.

2.2. Literature Review

Several MCDM algorithms have been proposed in the literature over the years. One of these algorithms is the technique for order preference by similarity to the ideal solution (TOPSIS) algorithm proposed by Hong and Choi [24]. This algorithm aims to find the best alternatives that have the smallest distances from the positive ideal solution. Many researchers have used the TOPSIS method for decision-making since its invention and have extended this algorithm to fuzzy and soft sets environments. To deal with fuzzy information in decision problems, Chen [25] extended conventional TOPSIS to fuzzy TOPSIS. In this paper, the linguistic description of criteria weighting and possibility evaluation is provided. Since then, the extended fuzzy TOPSIS algorithm has been adopted by a larger number of industries, including management, human resources, and logistics.

Bottani and Rizzi [26] have proposed the fuzzy TOPSIS method for logistic services. The interval-valued fuzzy TOPSIS method was proposed by Ashtiani et al. [27] to solve MCDM problems where the weights of the criteria are unequal, using the concept of interval-valued fuzzy sets and fuzzy TOPSIS. Ghassemi and Danesh [28] used fuzzy AHP and TOPSIS methods for desalination process selection and applied the TOPSIS algorithm for virtual enterprise partner selection. Baliaoti et al. [29] mentioned the multi-criteria

TOPSIS method under the fuzzy method along with the analytic hierarchy process (AHP) to evaluate the criteria and weights in their research.

Gulzar et al. [30] have presented a new framework using fuzzy logic that focuses on mapping attributes of usability requirements to user ratings. This framework prioritizes the conflicting usability requirements. For this purpose, they used the MATLAB fuzzy logic toolbox. Mustafa et al. [31] showed a different direction of the fuzzy decision algorithm. Based on logistic processes, they developed a multi-criteria structural model for retail facility location selection. Mathew et al. [32] reported a novel algorithm that integrates AHP and TOPSIS under a spherical fuzzy set for advanced manufacturing facility selection. The advantage of using a soft set is that it includes the deficit parameterization tools. The use of type 1 fuzzy sets still leads to uncertainties. Therefore, type-2 fuzzy sets are introduced to solve the mentioned problem. Therefore, Lathamaheswari et al. [33] considered a triangular interval fuzzy set of type-2 by combining a soft set and a triangular interval fuzzy set of type-2. In their work, the authors proposed a triangular interval type-2 fuzzy soft weighted arithmetic operator (TIT2FSWA). They used this method in decision problems for profitability analysis.

Wan et al. [34] explained decision-making with incomplete interval multiplicative preference relation (IMPRS). Salsabeela and John [35] extended TOPSIS with a Fermatean fuzzy soft set to solve MCDM problems. Insurance programs can provide relief to farmers in disaster situations, but farmers face several hurdles in selecting the best insurance package. Chu and Le [36] proposed a FAHP algorithm to solve this problem. It evaluates and selects the best insurance package for agricultural insurance using the ranking method. They demonstrated and validated the feasibility of this predictive method by numerical comparison. Mng'ong'o et al. [37] implemented the fuzzy TOPSIS method to evaluate the performance of agricultural crops and rank them in sustainable agriculture tanzania (SAT). They believe that there is an urgent need to emphasize the improvement of low-performance products by finding ways to improve low-weight criteria.

Mustafa et al. [38] investigated the bipolar fuzzy sets and used it to cover the positive as well as negative aspects of a specific symptom. It is combined with the idea of soft sets, which gives more precise results. Uncertainty and ambiguity are common features of decision-making difficulties. Many researchers worldwide have developed and advocated various methods for solving problems related to uncertainty. Zadeh [39] first pioneered the concept of fuzzy sets to deal with problems involving uncertainty and ambiguity. Chen et al. [40] introduced several fuzzy methods. Well-known and often helpful algorithms for modeling vagueness include the intuitionistic fuzzy set theory [41], the rough set theory [42], the vague set theory [24] and the theory of interval mathematics by Alefeld and Mayer at [43]. Each of these theories is fraught with problems that have already been discussed in [23].

Molodtsov [23] initiated a soft set as a broad mathematical tool for dealing with an indeterminate, fuzzy and ambiguous object without difficulty. Research in the field of soft sets has been very active, and many results have been obtained. Maji et al. [44] extended the previous work on soft sets and developed certain operations based on their properties. Feng et al. [45] used the theory of soft sets to solve a decision problem. Ma et al. [46] improved the Maji method for soft sets and created several additional operations using their properties. In another study, Zulqarnain et al. [47] discussed soft sets and the TOPSIS method with some new definitions and examples. Type-2 soft sets, an extension of Molodtsov's soft set, were proposed to deal with parameter associations.

Chatterjee et al. [21] initially discussed type-2 soft sets, which has not been studied or documented by any other researchers. The researchers investigated and analyzed various operations and their properties with mapping. In another paper, [48], the authors identified some limitations of some prevailing distance measures for type-1 soft sets and proposed new distance measures. The research demonstrated the utility of one of the proposed measures as an effective decision-making tool. Hayat et al. [49] discussed new operations for type-2 soft sets and their properties using de Morgan's law.

The summary of the literature review shown in Table 1 reveals the following research gaps.

1. The comparison between the decision-making tools is not based on specific criteria that cause a conflict of opinion and inaccurate results.
2. In the previous literature, the multi-criteria decision-making problem specified that the chosen parameters could be adjusted, which causes uncertainty due to the increased sample size.
3. In the decision-making problem, uncertainty in obtaining weights is adjusted by a subjective and objective strategy. The consistency of the judgment is maintained by using Euclidean distances without taking into account the relationship among the attributes. The Euclidean distance has the disadvantage that it assumes a circular distribution of the sample centroids around the sample mean.

Table 1. Summary of literature review

Study	Publication Year	Technique	Limitation(s)
[26]	2006	Fuzzy TOPSIS method for logistic services	The selection tree need to be developed into a multi-tier hierarchy to address the relationships between the upper and lower tier
[27]	2009	Interval-valued fuzzy TOPSIS method	Proposed MCDM applies to unequal weights. This could introduce bias or skew the results.
[45]	2010	Soft sets theory to solve a decision problem	Uncertainty in multi-criteria decision-making
[28]	2013	Fuzzy AHP and TOPSIS methods	Ineffective MCDM process caused by uncertainty because of increased sample size
[21]	2015	Type-2 soft sets	Relationship among decision-making attributes is not considered
[48]	2016	Proposed new distance measures	Effectiveness and accuracy of may be a limitation depending on the context of application
[30]	2017	A new framework using fuzzy logic focusing on mapping attributes of usability requirements	Lack of criteria for the prioritization of conflicting usability requirements attributes
[49]	2018	Type-2 soft sets using de Morgan's law	Parameters adjustment affects the multi-criteria decision-making
[29]	2018	Multi-criteria TOPSIS method under fuzzy along with the analytic hierarchy process	Uncertainty in decision-making
[31]	2019	Multi-criteria structural model on the basis of logistic processes	Parameters adjustment leads to uncertainty
[47]	2020	Soft sets and the TOPSIS method	Parameters adjustment leads to uncertainty caused and relationship among attributes is not considered
[32]	2020	A novel algorithm that integrates AHP and TOPSIS under a spherical fuzzy set	Integration of AHP and TOPSIS with a spherical fuzzy set increases the complexity
[33]	2020	A triangular interval type-2 fuzzy soft weighted arithmetic operator	Lack of generalization as it is specific to decision-making problems for profit analysis.
[34]	2021	Decision-making with incomplete interval multiplicative preference relation	Increase in uncertainties as the sample size grows
[35]	2021	Extend TOPSIS with a Fermatean fuzzy soft set	Lack of any particular criteria for decision-making
[36]	2022	FAHP algorithm to solve MCDM problems	Does not consider the relationship among attributes
[37]	2022	Fuzzy TOPSIS method to evaluate the performance of agricultural crops	Increase in sample size leads to uncertainties

Table 1. Cont.

Study	Publication Year	Technique	Limitation(s)
[38]	2023	Bipolar fuzzy sets used to cover the positive and negative aspects of a specific symptom	No specific criteria for decision-making
Our	2024	Proposed FMCDM using type-2 soft sets with TOPSIS	-

To achieve precision and preference in decision problems, we proposed FMCDM using type-2 soft sets with TOPSIS to solve the pesticide selection problem, described in Section 3. We named the proposed model MultiFuzzTOPS, as it is a technique or methodology that combines fuzzy logic with TOPS for decision-making processes, where the data or preferences are uncertain or imprecise. TOPSIS stands for technique for order preference by similarity to ideal solution. The MultiFuzzTOPS model aims to provide a more robust decision-making framework in complex and uncertain environments using fuzzy type-2 soft sets. Frequently used acronyms and their descriptions are given in Table 2.

Table 2. Acronyms and their descriptions.

Acronym	Description
a_j	Attributes of primary parameters
c_j	Attributes of underlying parameters in type-2 soft sets (F, A)
d_i	Attributes of underlying parameters in type-2 soft sets (G, B)
S_1	Triazoles spray
S_2	Strobilurin spray
S_3	Mancozeb spray
S_4	Propiconazole spray
P_1	Primary parameters
P	Production effect
T	Time of reaction
E	Environment effect
EH	Effect on human health
P_2	Underlying parameters
s	Soil effect
EW	Effect on water
AL	Animal life effect
C	Cost of Sprays
T2SS	Type-2 soft sets
FMCDM	Fuzzy multi-criteria decision-making
TOPSIS	Technique for order preference by similarity to ideal solution
MultiFuzzTOPS	A fuzzy multi-criteria decision-making model using type-2 soft sets and TOPSIS

3. Proposed Fuzzy MultiFuzzTOPS Model Using Type-2 Soft Sets with TOPSIS

The problem of deciding which pesticide is best from all points of view remains a challenge. To solve this problem, in this study, we propose a fuzzy MultiFuzzTOPS decision-making model using type-2 soft sets with TOPSIS to solve the problem of uncertainty in pesticide selection.

The algorithm for the proposed fuzzy MultiFuzzTOPS model includes the following steps:

- Step 1: Input the T2SS, T2SS, T2SS and T2SS.
- Step 2: Compute a tabular representation of the $(F, A), (G, B), (H, C)$ and (I, D) .
- Step 3: Construct a weighted decision matrix for each of $(F, A), (G, B), (H, C)$ and (I, D) for the underlying parameters.
- Step 4: Compute the weighted decision matrix for each of $(F, A), (G, B), (H, C)$ and (I, D) for the primary parameters.
- Step 5: Combine all decision makers' values in the final table.
- Step 6: Determine the positive ideal solution (PIS) and negative ideal solution (NIS).
- Step 7: Calculate the normalized Hamming distance.
- Step 8: Calculate the scores of alternatives with the help of positive and negative Hamming distances.
- Step 9: Rank the alternative by arranging the values in descending order.

In the following subsection, we demonstrate the mathematical problem formulation of the above algorithm.

3.1. Mathematical Problem Formulation

Step 1: Consider that $(F, A) = \{c_1 = \frac{u_k(a_j, c_i)}{a_j}\}$, $(G, B) = \{d_i = \frac{u_k(a_j, d_i)}{a_j}\}$, $(H, C) = \{e_i = \frac{u_k(a_j, e_i)}{a_j}\}$ and $(I, D) = \{f_i = \frac{u_k(a_j, f_i)}{a_j}\}$ are the four type-2 soft sets, where a_j are the attributes of primary parameters, and c_j are the attributes of underlying parameters in type-2 soft sets (F, A) , where a_j are the attributes of the primary parameters and d_i are the attributes of the underlying parameters in type-2 soft sets (G, B) .

Step 2: Compute the tabular representation of the above type-2 soft sets $(F, A) = \{c_1 = \frac{u_k(a_j, c_i)}{a_j}\}$, $(G, B) = \{d_i = \frac{u_k(a_j, d_i)}{a_j}\}$, $(H, C) = \{e_i = \frac{u_k(a_j, e_i)}{a_j}\}$ and $(I, D) = \{f_i = \frac{u_k(a_j, f_i)}{a_j}\}$ according to the decision maker.

Step 3: After computing the tabular representation of type-2 soft sets weights assigned by the decision maker, then construct the decision matrix for underlying parameters as per Equation (1):

$$D = [d_{ij}]_{m \times n} \quad (1)$$

$$D = \begin{matrix} & \begin{matrix} z_1 & z_2 & \vdots & z_n \end{matrix} \\ \begin{matrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{matrix} & \begin{matrix} \\ \\ \\ \end{matrix} \end{matrix} \Bigg]_{m \times n}$$

Step 4: After the weights are assigned by the decision maker for the underlying parameters, then construct the weighted decision matrix for primary parameters as shown in Equation (2):

$$W = [w_{ij}]_{m \times n} \quad (2)$$

$$W = \begin{matrix} & \begin{matrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m1} & w_{m2} & \cdots & w_{mn} \end{matrix} & \begin{matrix} \\ \\ \\ \end{matrix} \end{matrix} \Bigg]_{m \times n}$$

Step 5: Find a positive ideal solution (PIS) as per Equations (3) and (4):

$$P^+ = \{P_1^+, P_2^+, \dots, P_n^+\} \quad (3)$$

$$y_i^+ = \max(y_{ij}) \quad (4)$$

Find the negative ideal solution (NIS) as per Equations (5) and (6):

$$P^- = \{y_1^-, y_2^-, \dots, y_n^-\} \quad (5)$$

$$y_i^- = \max(y_{ij}) \quad (6)$$

Step 6: Next, find the normalized Hamming distance of each alternative from the positive ideal solution and calculate it as the following equation:

$$N_i^+ = \frac{1}{mnp} \left| \sum_{j=1}^m \sum_{i=1}^n \sum_{k=1}^p (y_{ij} - y^+) \right| \quad (7)$$

The normalized Hamming distance from the negative ideal solution (NIS) can be found using the following Equation (8):

$$N_i^- = \frac{1}{mnp} \left| \sum_{j=1}^m \sum_{i=1}^n \sum_{k=1}^p (y_{ij} - y^-) \right| \quad (8)$$

where m is the number of primary parameters, n is the number of underlying parameters, and p is the number of alternatives.

Step 7: Calculate the scores of alternatives with the help of positive and negative normalized Hamming distances as per the following Equation (9):

$$S_i^- = \frac{N_i^+}{N_i^+ + N_i^-} \quad (9)$$

Step 8: Rank the alternatives by arranging the values in descending order (S_i^+), then find the best alternative among the others.

3.2. Pseudo-Code of the Fuzzy MultiFuzzTOPS Model

The pseudo-code of the proposed MultiFuzzTOPS is demonstrated in this subsection.

Step 1: Start.

Step 2: Obtain the number of parameters and number of objects respectively $[m, u]$.

Step 3: Input the primary and secondary parameters and object pairs shown in Equation (10):

$$u_k(a_j, c_i), u_k(a_j, d_i), u_k(a_j, e_i) \text{ and } u_k(a_j, f_i) \quad (10)$$

where u_k no. of alternatives are based on a_j and c_i , the primary and underlying parameters in type-2 soft sets (F, A) ; u_k no. of alternatives are based on a_j and d_i , the primary and underlying parameters in type-2 soft sets (G, B) ; u_k no. of alternatives are based on a_j and e_i , the primary and underlying parameters in type-2 soft sets (H, C) ; and u_k no. of alternatives are based on a_j and f_i , the primary and underlying parameters in type-2 soft sets (I, D) .

Step 4: Multiply each underlying value by weights and add the underlying values by using Equation (11):

$$[\sum u_k, (a_j, c_i)], [\sum u_k, (a_j, d_i)], [\sum u_k, (a_j, e_i)] \text{ and } [\sum u_k, (a_j, f_i)] \quad (11)$$

Step 5: Multiply each primary value by weights, then add the primary values by using Equation (12):

$$[\sum u_k, (a_j, c_i)], [\sum u_k, (a_j, d_i)], [\sum u_k, (a_j, e_i)] \text{ and } [\sum u_k, (a_j, f_i)] \quad (12)$$

Step 6: After multiplying each parameter, we make the final decision matrix.

Step 7: Determine the highest and lowest values for each column. When using Equations (3)–(6), the maximum value is called the positive ideal solution (PIS) and the minimum value is called the negative ideal solution (NIS).

Step 8: Calculate the differences between the positive ideal value with each value of the final decision matrix. Similarly, calculate the difference between the negative ideal value with each value of the final decision matrix by using Equations (7) and (8).

Step 9: Calculate the scores of alternatives with the positive Hamming distance and negative Hamming distance by using Equation (9).

Step 10: Rank the alternative by arranging the values in descending order (S_i^+), then find the best alternative among the others.

Step 11: Stop

The flowchart shown in Figure 1 is a pictorial representation of the steps in sequential order. This flowchart shows our proposed MultiFuzzTOPS model, with input coming from the decision maker's observation and directly from farmers as end users.

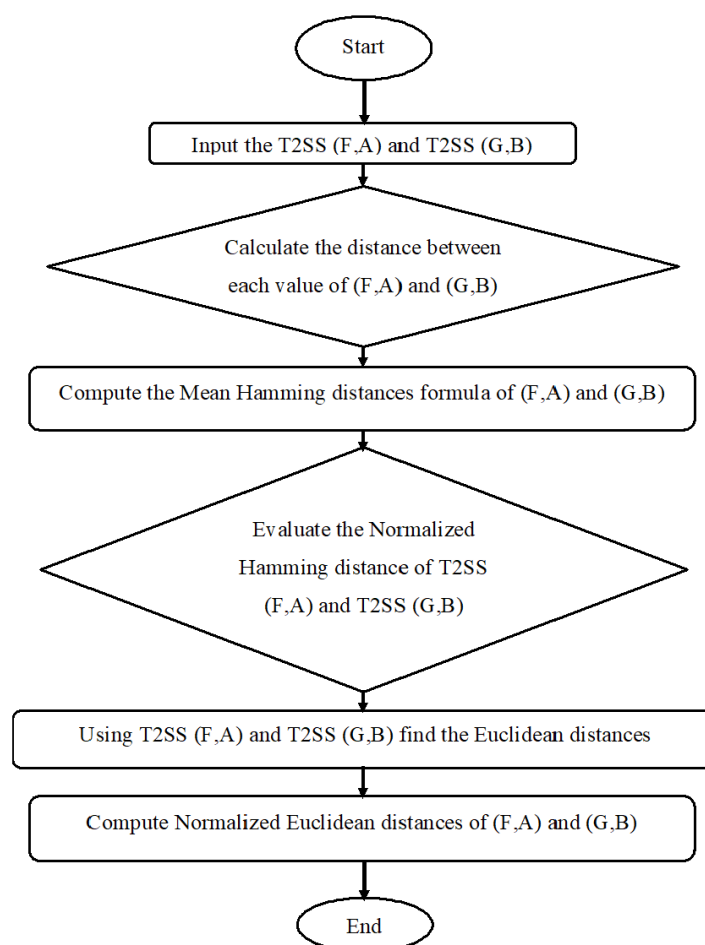


Figure 1. Flowchart of proposed MultiFuzzTOPS model using type-2 soft sets with TOPSIS.

4. Numerical Computations

A multi-criteria decision-making method in a fuzzy environment is used to select the best pesticides for end users. The present study is based on primary data collection, where the data were collected from decision makers who are alumni in forms. For the application of the type-2 soft set decision algorithm, the TOPSIS model is used to evaluate and select the most suitable pesticides for end users. Different criteria are developed for selecting the best pesticides among four alternatives: Triazoles spray (S_1), Strobilurin spray (S_2), Mancozeb spray (S_3), and Propiconazole spray (S_4).

4.1. Selection Criteria

Yellow rust is one of the most critical wheat diseases that destroys the leaves and stems of wheat plants and affects wheat production. Therefore, farmers want to select

pesticides to combat yellow rust disease. Here, we collect data from an end user or farmer. The selection of type-2 parameters depends on the preferences and needs of farmers. The primary parameters are as follows: P shows the production effect, T shows the response time, E shows the environmental effect, EH shows the effect on human health and the underlying parameters, S shows the soil effect, EW shows the effect on water, AL shows the effect on animal life, and C shows the cost of spraying. Each primary parameter and each underlying parameter was assigned a weight. A group of four decision makers (D_1 , D_2 , D_3 , and D_4) were asked to provide their judgments, which are shown in Table 3.

Table 3. Judgment weights of decision makers D_1 , D_2 , D_3 , and D_4 .

Decision Maker 1 (D_1)				Decision Maker 2 (D_2)			
Primary Parameters Weights		Underlying Parameters Weights		Primary Parameters Weights		Underlying Parameters Weights	
P	0.4	S	0.1	P	0.35	S	0.45
T	0.3	EW	0.2	T	0.45	EW	0.25
E	0.1	AL	0.5	E	0.1	AL	0.01
EH	0.2	C	0.3	EH	0.1	C	0.29
Decision Maker 3 (D_3)				Decision Maker 4 (D_4)			
Primary Parameters Weights		Underlying Parameters Weights		Primary Parameters Weights		Underlying Parameters Weights	
P	0.5	S	0.7	P	0.55	S	0.2
T	0.35	EW	0.01	T	0.2	EW	0.8
E	0.05	AL	0.1	E	0.04	AL	0.22
EH	0.1	C	0.19	EH	0.21	C	0.5

4.2. Implementation Details of Proposed MultiFuzzTOPS

Step 1: Here, we take four known sprays as alternatives: triazole spray (S_1), strobilurin spray (S_2), mancozeb spray (S_3), and propiconazole spray (S_4). We take four decision makers D_1 , D_2 , D_3 , and D_4 , and four primary parameters: production effect (P), time of reaction (T), environment effect (E), and effect on human health (EH), and four underlying parameters: soil effect, effect on water, effect on animal life, and cost of sprays:

$$D = \{D_1, D_2, D_3, D_4\} \quad \text{Decision maker}$$

$$S = \{S_1, S_2, S_3, S_4\} \quad \text{Sprays as alternatives}$$

where S_1 = Triazoles spray, S_2 = Strobilurin spray, S_3 = Mancozeb spray, and S_4 = Propiconazole spray.

Primary parameters (P_1) = Production effect (P), Time of reaction (T), Environment effect (E), and Effect on human health (EH).

Underlying parameters (P_2) = soil effect(S), effect on water (EW), animal life effect (AL), and cost of Sprays (C).

The first decision maker D_1 chooses the set of underlying parameters with respect to the primary parameters for the selection of sprays and constructs the type-2 soft set (F, A):

$$F(P) = \left\{ \frac{S}{S_3}, \frac{EW}{S_1}, \frac{AL}{S_2} \right\}$$

$$F(T) = \left\{ \frac{EW}{S_1, S_2}, \frac{AL}{S_3, S_4} \right\}$$

$$F(E) = \left\{ \frac{S}{S_1, S_2}, \frac{C}{S_3, S_4} \right\}$$

$$F(EH) = \left\{ \frac{EW}{S_1, S_3, S_4}, \frac{AL}{S_2}, \frac{C}{S_1} \right\}$$

In the above-mentioned type-2 soft sets, according to decision maker D_1 , S shows the soil, S_3 shows the Mancozeb spray with primary parameters, and P (production) shows the willingness of the decision maker. The second decision maker D_2 chooses the underlying parameters with respect to the primary parameters for the selection of the sprays and constructs the type-2 soft set (G, B)

$$F(P) = \left\{ \frac{EW}{S_2, S_3}, \frac{AL}{S_1}, \frac{C}{S_4} \right\}$$

$$F(T) = \left\{ \frac{S}{S_1, S_4}, \frac{EW}{S_2, S_3} \right\}$$

$$F(E) = \left\{ \frac{S}{S_1}, \frac{AL}{S_2, S_4}, \frac{C}{S_3} \right\}$$

$$F(EH) = \left\{ \frac{S}{S_3}, \frac{EW}{S_1, S_2, S_4} \right\}$$

In the above-mentioned type-2 soft sets, according to the decision maker D_2 , E shows the environment effect, S_3 shows the Mancozeb spray with the primary parameters, and P (production) shows the willingness of the decision maker. The third decision maker D_3 chooses the underlying parameters with respect to the primary parameters for the selection of the sprays and constructs the type-2 soft set (H, C) :

$$F(P) = \left\{ \frac{S}{S_2}, \frac{AL}{S_3, S_4}, \frac{C}{S_1} \right\}$$

$$F(T) = \left\{ \frac{S}{S_2}, \frac{EW}{S_1, S_3}, \frac{AL}{S_4} \right\}$$

$$F(E) = \left\{ \frac{EW}{S_2}, \frac{AL}{S_1, S_3}, \frac{C}{S_4} \right\}$$

$$F(EH) = \left\{ \frac{S}{S_2, S_3}, \frac{EW}{S_1}, \frac{C}{S_4} \right\}$$

In the above-mentioned type-2 soft sets, according to the decision maker D_3 , EH shows the effect of health, S_2 shows the Strobilurin spray with primary parameters AL(animal effect) shows the willingness of the decision maker. The fourth decision maker D_4 chooses the underlying parameters with respect to the primary parameters for the selection of the sprays and constructs the type-2 soft set (I, D) :

$$F(P) = \left\{ \frac{S}{S_1, S_4}, \frac{AL}{S_2}, \frac{C}{S_3} \right\}$$

$$F(T) = \left\{ \frac{S}{S_3}, \frac{EW}{S_2}, \frac{AL}{S_4}, \frac{C}{S_1} \right\}$$

$$F(E) = \left\{ \frac{S}{S_2}, \frac{EW}{S_1, S_3}, \frac{AL}{S_4} \right\}$$

$$F(EH) = \left\{ \frac{S}{S_4}, \frac{EW}{S_2}, \frac{AL}{S_3}, \frac{C}{S_1} \right\}$$

Step 2: After that, with the assistance of the four decision makers, we create the type-2 soft sets. We construct the decision matrix with the help of underlying parameters for primary parameters. In this step, we multiply each value with the associated weights and then add the scores. After applying the type-2 soft sets of decision maker 1, decision maker 2, decision maker 3, and decision maker 4, we have the underlying parameters Tables 4–7, related to the primary parameter, the production effect (P).

Table 4. D_1 scores of the sprays, for the primary parameter (P).

Weights	0.1	0.2	0.5	0.3	
Sprays/Underlying Parameters	S	EW	AL	C	Scores
S_1	0	1	0	0	0.2
S_2	0	0	1	0	0.5
S_3	1	0	0	0	0.1
S_4	0	1	0	0	0.2

Table 5. D_2 Scores of the sprays, for the primary parameter (P).

Weights	0.45	0.25	0.01	0.29	
Sprays/Underlying Parameters	S	EW	AL	C	Scores
S_1	0	0	1	0	0.01
S_2	0	1	0	0	0.25
S_3	0	1	0	0	0.25
S_4	0	0	0	1	0.29

Table 6. D_3 scores of the sprays, for the primary parameter (P).

Weights	0.7	0.01	0.1	0.19	
Sprays/Underlying Parameters	S	EW	AL	C	Scores
S_1	0	0	0	1	0.19
S_2	1	0	0	0	0.7
S_3	0	0	1	0	0.1
S_4	0	0	1	0	0.1

Table 7. D_4 scores of the sprays, for the primary parameter (P).

Weights	0.2	0.8	0.22	0.5	
Sprays/Underlying Parameters	S	EW	AL	C	Scores
S_1	1	0	0	0	0.2
S_2	0	0	1	0	0.22
S_3	0	0	1	1	0.72
S_4	1	0	0	0	0.2

Step 3: Compute the weighted decision matrix for each decision maker for the primary parameters.

By calculating the underlying parameters, after computing the weighted decision matrix of each decision maker for primary parameters, we combine all decision maker's values in one table, which is the weighted decision matrix as shown in Table 8.

Table 8. Weighted decision matrix.

Sprays/Decision Maker	D1	D2	D3	D4
S_1	0.19	0.8855	0.1045	0.347
S_2	0.37	0.3565	0.6655	0.457
S_3	0.26	0.4055	0.195	0.5142
S_4	0.3	0.9395	0.1135	0.3098

Step 4: Find the ideal negative and positive ideal solution (NIS and PIS, respectively).

In the weighted decision matrix, for each decision maker, the distinct smallest and extreme values, we have calculated positive ideal solution and negative ideal solution as described in Table 9.

Table 9. Positive ideal solution (PIS) and negative ideal solution (NIS).

Sprays	PIS	NIS
S_1	0.8855	0.1045
S_2	0.6655	0.3565
S_3	0.5142	0.195
S_4	0.9395	0.1135

Step 5: Calculate the normalized Hamming distances.

After the calculation of PIS and NIS, we calculate the Hamming distance from the positive ideal solution (HPD) and the Hamming distance from the negative ideal solution (HND) as shown in Table 10.

Table 10. Calculation of Hamming distance from the positive ideal solution (HPD) and Hamming distance from the negative ideal solution (HND).

Sprays	HPD	HND
S_1	0.031484	0.017328
S_2	0.012703	0.006609
S_3	0.010658	0.009292
S_4	0.032738	0.018888

Step 6: Calculate the closeness coefficient (CC) of the alternatives.

We achieved our goal of selecting the best alternative. The closeness coefficient and ranking of alternatives is shown in Table 11.

Table 11. Closeness coefficient (CC) and ranking of alternatives.

Sprays	CC	Rank
S_1	0.645006	2
S_2	0.657767	1
S_3	0.534226	4
S_4	0.63414	3

Figure 2 shows that the highest rank is assigned to the maximum value, so the maximum value is 0.6577 and obtains a rank of order 1, which represents the best pesticide as compared to the others.

Step 7: Rank the alternative by arranging the values in ascending order (S_i^+).

After evaluating the closeness coefficient (CC), we conclude that $S_2 > S_1 > S_4 > S_3$. Consequently, Strobilurin spray (S_2) is the best spray overall. The next section validates the accuracy of the proposed algorithm through comparative and sensitivity analysis.

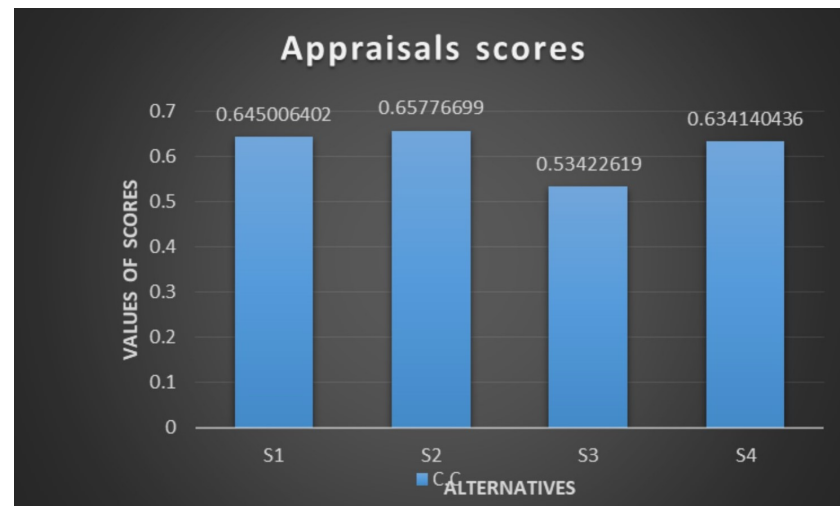


Figure 2. Ranking of pesticides.

5. Sensitivity and Comparative Analysis of Our Proposed Model

5.1. Sensitivity Analysis

Sensitivity analysis is a systematic review that involves decision-making procedures applied to pre-determined investigations to evaluate the results of the entire process under study and reach a conclusion. In our case, a sensitivity analysis is performed to verify the accuracy of the proposed pesticide selection algorithm for end users. The sensitivity analysis is applied to the same alternative for pesticide selection. The decision maker is again asked to weight the four alternatives to review the overall process and make the final decision on the proposed work.

Weights Assigned by the Decision Makers

The choice of type-2 soft sets of parameters depends on the preferences and needs of farmers. Here, the primary parameter P shows the production effect, T the response time, E the environmental effect, EH the human health effect, the underlying parameter S the soil effect, EW the water effect, AL the animal life effect, and C the cost of spraying. The four decision makers (D_1 , D_2 , D_3 , and D_4) were again asked to assign weights, which are shown in Table 12. The weights for the primary parameters and the underlying parameters were assigned independently for the selection of pesticides.

By applying the same steps by using the equation, we calculated the type-2 soft sets positive ideal solution and negative solution. We calculated the normalized Hamming distances and found the closeness coefficient. The results are presented in Figure 3.

Table 12. Weights assigned by the decision makers D_1 , D_2 , D_3 , and D_4 .

Decision Maker 1 (D_1)				Decision Maker 2 (D_2)			
Primary Parameters Weights		Underlying Parameters Weights		Primary Parameters Weights		Underlying Parameters Weights	
P	0.19	S	0.45	P	0.3	S	0.1
T	0.1	EW	0.1	T	0.5	EW	0.5
E	0.01	AL	0.35	E	0.2	AL	0.35
EH	0.007	C	0.1	EH	0.1	C	0.05

Table 12. Cont.

Decision Maker 3 (D_3)				Decision Maker 4 (D_4)			
Primary Parameters Weights		Underlying Parameters Weights		Primary Parameters Weights		Underlying Parameters Weights	
P	0.22	S	0.7	P	0.45	S	0.2
T	0.1	EW	0.01	T	0.25	EW	0.8
E	0.46	AL	0.1	E	0.01	AL	0.22
EH	0.2	C	0.19	EH	0.29	C	0.05

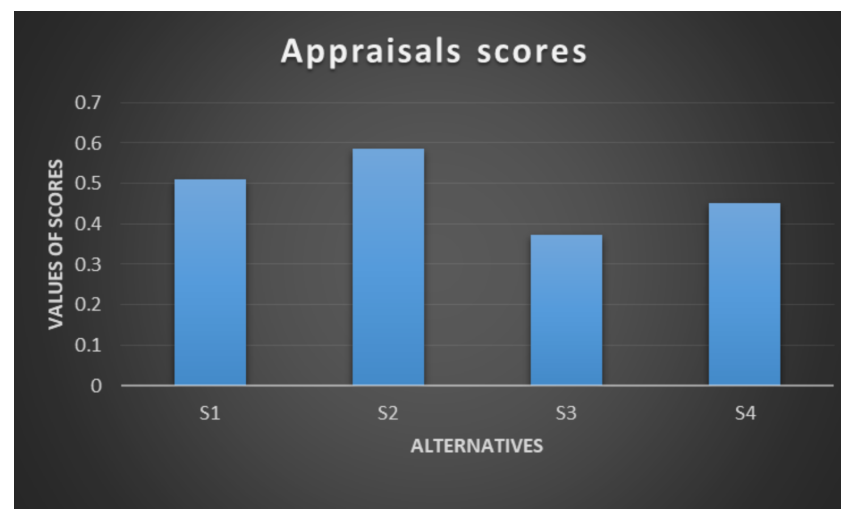


Figure 3. Scores of alternative sprays.

5.2. Comparative Analysis

A comprehensive comparison of our proposed algorithm with the existing algorithms is given in Table 13 that proves the significance and accuracy of our proposed algorithm for effective and efficient pesticide selection.

Table 13. Comparative analysis of our proposed fuzzy MCDM algorithm with existing studies [21,47,49].

Reference	Technique	Conflict of Opinion	Inaccuracy of Results	Sub-Attributes on a Priority Basis	Loss of Data
[21]	Type-2 Soft sets	✓	✓	X	X
[49]	Type-2 Soft sets	✓	✓	✓	X
[47]	TOPSIS with soft sets technique	✓	✓	X	✓
Our proposed MultiFuzzTOPS model	TOPSIS with type-2 soft sets	X	X	✓	X

The results shown in Table 13 prove that our proposed algorithm gives optimal and better results compared to the existing algorithms. Chatterjee et al. [21], studied type-2 soft sets at the very beginning, but they only focused on the operations and their properties using mapping. Their research does not address the proper selection of strategies and the order of attributes. Another research study, by Hayat et al. [49], also studied operations in soft sets of type 2 and their attributes using de Morgan's law, but this also did not lead to the correct results. From the table, it can be seen that Zulqarnain et al. [47] used the soft sets and TOPSIS method, but due to the Euclidean distance, only the sample mean was used,

which led to disagreement and inaccurate results due to lack of information. Compared to the existing algorithms, the proposed algorithm covers all the information due to the Hamming distance, which leads to more precise and accurate decisions in the result. After comparing the existing models, the proposed model strengthens our results and proves to be more advantageous and productive.

6. Real Life Applicability and Limitations of the Proposed Model

6.1. Real Life Applicability of the Proposed Model

The type-2 soft set method provides a powerful approach for dealing with uncertainty in real-world problems, especially in scenarios where decision-making is critical but uncertainty exists. In real life, practitioners can apply type-2 soft sets to analyze different options and the associated uncertainties. In the current study, the T2SS method is applied to the pesticide selection problem, i.e., a real-life problem. Moreover, in financial investment decisions, for example, where market fluctuations lead to uncertainty, this method can help to evaluate the trade-off between risk and return more effectively.

6.2. Limitations of the Study

The limitation of our study is that the experts/decision makers must be carefully selected because the decision-making process depends on the knowledge of the experts and the number of participants. In the future, new assessment factors could be considered, especially regarding biodiversity control, which could influence the assessment process and pesticide selection to improve the robustness of the results. In addition to the Multi-FuzzTOPS, other algorithms such as GIS can be implemented to study soil properties at different sites and evaluate the applicability of a particular selected pesticide accordingly. In this way, a reference model can be created to check the similarity of the ranking of pesticides at different sites. It would certainly be a great effort to help farmers to select a suitable pesticide.

7. Conclusions and Future Work

Pesticides play a very important role in the agriculture sector; however, choosing the best pesticide remains a major problem for farmers. Based on the basic idea of symmetry to balance the arrangement where elements or features are equally or similarly distributed, our proposed MultiFuzzTOPS model using type-2 soft sets with TOPSIS utilizes the current scientific knowledge from the literature and pesticide experts and recommends the optimal solution. Our proposed model employs preference information that leads to more comprehensive and accurate results. We ranked the results on the basis of the Hamming distance and similarity coefficient. The computational procedure in the proposed algorithm is different for determining an ideal solution because the legacy MCDM models are based on the extreme values that lead to information loss, but our proposed MultiFuzzTOPS model covers the maximum information for selecting the best alternative. Besides this, we have evaluated the closeness coefficient on the basis of the ranking and sensitivity analysis of $S_2 > S_1 > S_4 > S_3$ ($0.657767 > 0.645006 > 0.63414 > 0.534226$, respectively). Consequently, S_2 (Strobilurin spray) is the best alternative spray. The accuracy of the proposed technique for the selection of pesticides for end users was checked by sensitivity analysis which also proved that S_2 is the best alternative for the selection of pesticides. The results confirm the applicability of our proposed algorithm and confirm that the proposed algorithm is the best tool for pesticide selection in any agricultural field.

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