An Innovative Algorithm for Cluster-Based Decision Support System Using the Fuzzy Soft Set Approach

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Abstract. Hard sets and soft sets must be adopted for several unknown logistical problems. This paper seeks to solve the cluster-based decision-making dilemma effectively based on fumigated soft environments. First of all, we are introducing an adjustable approach to resolution of decisions focused on fuzzy soft solutions. Then, the information and the degree of divergence dependent on α-similarity are introduced to determine the weights of the experts. In addition, with uncertain expert weights, we can create an effective cluster-based decision-making strategy. Finally, sensitivity analysis and comparative analysis was conducted with other established approaches.

Keywords: fuzzy soft set, decision making, cluster-based decision, decision support system.

1. Introduction

In the new definition of generalization of intuitive fugitive soft sets, an intuitive soft, soft set over the world of debate and an intuitive fugue set in the set of parameters are clarified and reworked. This current approach defines two different categories of widely distributed intuitive soft subsets and different new functions for general soft sets. From this modern perspective, both intuitive and intuitive systems explain the top and bottom alternatives. These new ideas enhance some current performances and principles. Two binary links are suggested for comparing intuitive fuzzy values using the Expectation Score function. The algorithm is designed to solve several-attribute problems of decision making using a widespread intuitive fogging soft range, the expanded intersection, the intuitive, fuzzy weighted average operator and other similar ideas. The suggested algorithm would be explained in a case study on the topic of faculty appointments. Furthermore, the review of the viability and benefits of the newly designed process showed that a wide variety of paradigms have been developed in the last decades to study uncertainties. The analysis contrasts our approach. That include fizzy sets, robust sets and sleek sets with three classically unclear hypotheses. These soft computer tools excel in capturing key characteristics, which are graduality, granularity, and parameterization, of uncertainties depending on independent perspective. [1-7].

Differing uncertainties should be handled in an integrated way because of the complexity of real-life processes. There have therefore been proposed several hybridizations with different soft computers. Mixing fluffy sets and smooth sets in particular. Fuzzy soft collections, fleeting and soft, have been released. Fuzzy sets of soft products have been analysed extensively and expanded in the theorems of decomposition to complex data analysis and decisions. Majumdar and Samanta defined and used general fuzzy medical soft sets. The definition of intuitive soft sets is implemented with intuitive fuzzy sets (IFSSs).
While decision-making based on intuitional, fuzzy soft sets with numerous attributions permits one to take the hesitation of experts into account in the evaluation of alternatives, this hesitation relies solely on the subjective perception of experts who judge it and must therefore be further examined in certain crucial circumstances. In order to deal with this challenge, Agarwal et al. has introduced and created a new paradigm called the generalised intuitionist soft sets (GIFSSs). You may use GIFSS-based models to compensate for any distortion of previously presented knowledge by experts using an additional intuitionist fluid feedback from a moderator. [8-15]

In the extensive fuzzy logic (FLe), set concepts and approximate reasoning constitute a systemic method for turning inaccurate knowledge into non-linear maps of what we define as the f-sets here. In comparison to the probable one, the f-set varies from the f-set when it concerns the limit of validity. Via F-Set we can work with two different ways of uncertainty at the same time: one linked to undefined, unfinished, ambiguous things, of which one or more is unclear/vague/partial/unspecific/unfinished. And another which is connected with incremental principles of reality. Here, new concepts for oscillation and \( \alpha \)-cuts are described, the theory of \( f \) extension introduced and arithmetic calculations in FLe considered.

In addition, the proposed FLe scheme addresses additional issues such as fluxing and validation operations during input, set-up and defuzzing in the output processing phase, and inferencing. Indeed, we plan to work with FLe from the stands of sets and structures technically and functionally to broaden the idea of an estimated reasoning. Consequently, we conclude that the degree to which approaches, and facts are true will lead to more reasonable and trustworthy results by achieving greater uncertainty.

Fuzzy Logic has been extensively analysed since the seminal paper on Fuzzy sets in 1965. The experiments indicate that fluid logic concepts very much coincide with rough reasoning that validated their ability to solve problems for the first time. In applying futile logic in the management of problems, the proven fact remains a vital criterion. In closed worlds like the shortest way from where to go this criterium can be met, but certain problems of the open world, such as finding the fastest path into a destination, do not satisfy this requirement. Fluid logic must be improved too in order to solve challenges of the open world. This is achieved by applying the FLu logic to fluid logic, which leads to a broader fluid logic (FLe). [16-20].

In applying fluffy logic to deal with challenges, the proved truth remains important. This criterion can be fulfilled in closed universes, such as the shortest route to a destination, but some open-world challenges, such as seeking the fastest route to a destination, cannot meet this requirement. Fluid logic can also be improved in order to address open-world problems. This improvement comes from the use of unintended, fluid logic (FLu) for fluid logic which leads to increased liquid logic (FLe). The way FLe is a very basic stand directed specifically at more detail aspects. We wish to develop numerous FLe notions from the sets and structures of this article that are logically and mathematically true. The approximate logic theory, names and sets, and the provision of computational methods in FLe in particular, are extended. We introduce to this a number of new theories, such as oscillate cuts, \( \alpha \)-talk cuts and the expansion (f-transform) of conceptual flight, for example f-sets and a theorem for extension. The meanings os-cut, and \( \alpha \)-to-cut are generally helpful methods in order to provide an S-response in the form of fluffy sets. The way FLe is a very basic stand directed specifically at more detail aspects. We wish to develop numerous FLe notions from the sets and structures of this article that are logically and mathematically true. The approximate logic theory, names and sets, and the provision of computational methods in FLe in particular, are extended. [21-25].

We introduce to this a number of new theories, such as oscillate cuts, \( \alpha \)-talk cuts and the expansion (f-transform) of conceptual flight, for example f-sets and a theorem for extension. The meanings os-cut and \( \alpha \)-to-cut are generally helpful methods in order to provide an S-response in the form of fluffy sets. The theory of \( f \)-extension requires the domain of a reference to be expanded from points in \( U \) in a
discourse $U$ universe to $f$-transformed subsets of $U$. For arithmetical operations in $FLe$, we use this theory. At that end, we introduce some new theories, such as the oscillation, $\alpha$-cutting and expanding ($f$-transforming) fluid principles as $f$-sets and the $f$-extension theorem. The concepts of os-cut and $\alpha$-to-cut are also helpful strategies for presenting an $S$-relating as flawed sets and crunchy sets. The $f$-extension theorem allows an expansion in a disc universe of the domain of a relation into $U$ sub-sets of $f$. The philosophy of the $f$-extension allows one to perform arithmetic activities within $FLe$ using this theory more. A FuzzyEn supported subspace solution, which can effectively solve defects in existing subspace filters, is proposed. An iterative soft threshold (FESIST) is available. Two synthetic disorderly series first demonstrate the system's effectiveness and then test it with genuine organic signals. The results indicate that the suggested approach was superior to the existing methods of sub-space filtering and analytical and wavelet decomposition. Fuzzy Entropy (FuzzyEn) is the result of an analysis in all disciplines of organised science systems, turbulence and chaos, information theory and fluid logic. [26-32].

FuzzyEn evaluates its complexity or irregularity in a nonlinear time series generated by a complex dynamic system. FuzzyEn's main facets are to measure the vector similarities and fluid probabilities using the swinging membership equation. The degree of complexity of the dynamic system is basically this measure. FuzzyEn was originally used to distinguish deterministic systems, like chaotic processes, from stochastic operations. The bivariate variant Cross-FuzzyEn (C-FuzzyEn) measures the time-sequence of sync and/or relation. In contrast with other chaotic invariants in the time series, FuzzyEn has a variety of positive elements, including higher monotony, relative reliability and improvement in sound robustness. In the fields of biomedical engineering, mechanical engineering, imaging, bioinformatics, geonomy, financials, and so on FuzzyEn applications were applied to signal and information processing. As it covers both deterministic and stochastic, linear and non-linear, stationary and non-linear outcomes, FuzzyEn has used FuzzyEn for online pre-seismic abnormality prediction. In several of these applications, the complexities Sampler Entropy (sample entropy) and Lempel-Ziv have been found to be above and above many other known nonlinear invariants, including approximate entropy (ApEn). As it covers both deterministic and stochastic, linear and non-linear, stationary and non-linear outcomes, FuzzyEn has used FuzzyEn for online pre-seismic abnormality prediction. In several of these applications, the complexities Sampler Entropy (sample entropy) and Lempel-Ziv have been found to be above and above many other known nonlinear invariants, including approximate entropy (ApEn). The second is to build a FuzzyEn-based subterranean detonation device to solve two permanent and critical issues with the filtering of subspace, the noise floor and the unchanged signal subparagraph. The depletion of the noise is an all-pervasive phenomenon. Each application that does not isolate any desired signal from noise or distortion such as cell signaling, speech recognition, imagery processing, biomedical signals processing, radar or sonar are major problems with reduced and removed noise and distortion. This is the format for the remainder of the post. Section 2 reviews any simple soft compound designs and compounds that are floating. In Section 3 a new remote method is used for the resolution of decisions. Section 4 recommends information measurement and an expert weight similarity ratio. An approach is then established that integrates the above approaches for decision making on a cluster basis. Section 5 is an example of how useful and functional the suggested approaches are. Finally, in Section 6, the results are presented.

2. Preliminaries
Here you will learn some basic notions of soft sets in the following pages. Maybe $U$ is the parameter set original and $E$ is the parameter set.

**Definition 2.1** (see [4]). The soft set over $U$ is considered a pair $(F, E)$, if $F$ mapped $E$ in all $U$ subsets. In other words, the soft set is a subclass of the set $U$, where the user identifies. The soft elements or the set of soft elements estimates can be considered for each $F (e E)$ set of this sequence.

With the inclusion of a fumbling set and a soft set the notion of a fuminous soft set was applied [5].
Definition 2.2 [5], [3]. Let U be the universe and let A be the parameter that has been set. The pair's soft fluid set over US is an F-pU pair, where the pair is F-pU. The pair is A-PU.

Development 2.3 [5], [4], [1]. The soft subassemblies of the Universes, and of the soft settings are f, a, and a, f, and faint, g, b, f, f; if a, faint B and A, f, and faint G. The soft subassemblies in F, A, f, f.

Example 2.1. You may consider Mr. X's fugitive soft package (F, E) to buy the 'home attraction'. This packet. Four worlds are being taken into account: U=h 1, h2, h3, H4, and E=e1, e2, e3, e4 parameters.

Table 1 presents the tabular shape of such a fluffy soft package.

Table 1.

|   | (F, E) | e1 | e2 | e3 | e4 |
|---|--------|----|----|----|----|
| h1 | 0.3    | 0.3| 0.2| 0.7|
| h2 | 0.4    | 0.5| 0.8| 0.3|
| h3 | 0.6    | 0.3| 0.6| 0.2|
| h4 | 0.3    | 0.5| 0.3| 0.1|

3. An Adjustable Approach to Fuzzy Soft Set-Based Decision-Making

In general, current approaches to gentle, faded decisions are mostly focused on different levels categories.
Politicians cannot therefore choose a suitable set of soft norms. When faced with policy problems, the greater the difference between the approach and the goal of the policy maker, the better the option. The simpler the option. Therefore, in this section we propose a balanced approach to fluffy soft-based decisions, with the difference between fluffy soft sets [32]. Then it’s. By this definition one can see that a soft and fluffy matrix coincides with one matrix, so that without a distinguishing difference we have a fluffy soft and fluffy soft matrix.

**Definition 3.1** (see [32]). Assume (F, E) and (G, E) to have two fluoridated sets over U and to define the difference between F, E and G.

\[
d((F,E),(G,E)) = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} |F(e_i)(x_j) - G(e_i)(x_j)|
\]  

(6)

Next, between these two fuzzy soft sets, we’re introducing new space to deal with weighted, soft decisions.

Definition 3.2. The two fuggish soft sets F, E and G, E, can be described as the interval between F, E and G.

\[
d((F,E),(G,E)) = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} p_i |F(e_i)(x_j) - G(e_i)(x_j)|
\]  

(7)

Where \( p_i = 1 - \omega_i \) and \( \omega_i \) respectively, 1 shall be the weight of the \( e_i \) parameter of \( i \).

The following characteristics can also be easily proved in (6) and (7)

\[
0 \leq d((F,E),(G,E)) \leq 1,
\]

\[
d((F,E),(G,E)) = 0 \iff (F,E) = (G,E),
\]

\[
d((F,E),(G,E)) = d((G,E),(F,E)),
\]

\[
(F,E) \subseteq (G,E) \subseteq (P,E), \iff d((F,E),(G,E)) \leq d((F,E),(P,E)), d((G,E),(P,E))
\]

\[
\leq d((F,E),(P,E)).
\]

We construct a decision-making problem-solving algorithm based on fuzzy soft sets below.

**Algorithm 1** (Fuzzy Soft Sets decision-making).

Input: Fuzzy soft set F, E over U, given in Table 2, where E is a set of parameters indicating \( E = e_1, e_2, \ldots, e_k, e_m \) and \( U \) is a first set of universes indicated in \( U = x_1, x_2, \ldots, x_n \). Input: Output: the order relationship of all options.

**Step 1.** Create a flawless soft range \( F_0, E \) with one single object \( x \) as seen in table 3.

**Step 2.** Get a furious soft set \( F_k, E_k = 1, 2, \ldots, n \) for the single alternative \( x_k \), as set out in Table 4.

**Step 3.** Difference between soft and fumigated set \( F_0, E \), Alternative \( 1 = 1, 2, \ldots, m \).

The bigger the d \( F_0, E, F_k, E \), the closest the \( F_k, E \) is to the perfect soft \( F_0, E \), the more obvious. \( x_k \)’s stronger, therefore.

**Step 4.** Place all alternatives in line with d \( F_0, E, F_k, E \) or d, E, Fk, E. Let us take the example below to better grasp the above theory.

E.g., 3.1. (see [14]). Let F, A be Table 5’s cosy soft package.

In order to score the options, we shall then use the proposed policy solution.

(1) Build the optimum Fuzzy Soft Set \( F_0, A \), as provided in Table 6, with a single alternative \( x \).

(2) On the basis of the above-mentioned soft-set F, A, we get the FK, A = 1, 2, 3 with the single alternative Xk as shown in Tables 7-9.

(3) Utilize (6) to get the distance d \( F_0, A, F_k, A \) k = 1, 2, 3:

\[
d((F_0, A), (F_1, A)) = 0.398
\]

\[
d((F_0, A), (F_2, A)) = 0.358
\]

\[
d((F_0, A), (F_3, A)) = 0.366
\]  

(9)

(4) Rank any options by distance d \( F_0, A, F_k, A \) k = 1, 2, 3. The order relation between all alternatives is then \( x_2 \) — by \( x_3 \) — by \( x_1 \), and the best alternative is \( x_2 \). The rating orders for the suggested system
and other approaches are shown in Table 10, as compared to the diverse decision-making procedures [12, 14, 15]. Therefore, in the proposed scheme and in the two other systems, Table 10 shows that three order rankings are the same, while alternative x2 constitutes the best choice [14,15]. However, the approach [12] is a different rating, and the x3 alternative is the stronger.

### Table 2: Fuzzy soft set (F, E)

| (F, E) | e1  | e2  | e3  | ... | em  |
|--------|-----|-----|-----|-----|-----|
| x1     | a11 | a12 | a13 | ... | a1m |
| x2     | a21 | a22 | a23 | ... | a2m |
| ...    | ... | ... | ... |     |     |
| xn     | an1 | an2 | an3 | ... | anm |

### Table 3: Ideal fuzzy soft set (F₀, E)

| (F₀, E) | e1  | e2  | e3  | ... | em  |
|---------|-----|-----|-----|-----|-----|
| x       | 1   | 1   | 1   | ... | 1   |

### Table 4: Fuzzy soft set (Fₖ, E)

| (Fₖ, E) | e1  | e2  | e3  | ... | em  |
|---------|-----|-----|-----|-----|-----|
| xₖ     | aₖ1| aₖ2| aₖ3| ... | aₖm|

### Table 5: Tabular representation of the fuzzy soft set (F, A)

| (F, E) | e1  | e2  | e3  | e4  | e5  |
|--------|-----|-----|-----|-----|-----|
| X₁     | 0.9 | 0.7 | 0.4 | 0.3 | 0.8 |
| X₂     | 0.6 | 0.8 | 0.8 | 0.6 | 0.4 |
| X₃     | 0.8 | 0.5 | 0.8 | 0.5 | 0.5 |

### Table 6: Ideal fuzzy soft set (F₀, A)

| (F₀, A) | e1  | e2  | e3  | e4  | e5  |
|---------|-----|-----|-----|-----|-----|
| x       | 1   | 1   | 1   | 1   | 1   |

### Table 7: Fuzzy soft set (F₁, A)

| (F₁, E) | e1  | e2  | e3  | e4  | e5  |
|---------|-----|-----|-----|-----|-----|
| X₁     | 0.9 | 0.7 | 0.4 | 0.3 | 0.8 |

### Table 8: Fuzzy soft set (F₂, A)

| (F₂, E) | e1  | e2  | e3  | e4  | e5  |
|---------|-----|-----|-----|-----|-----|
| X₂     | 0.6 | 0.8 | 0.8 | 0.6 | 0.4 |
Table 9: Fuzzy soft set (F_3, A)

| (F_3, E) | e_1 | e_2 | e_3 | e_4 | e_5 |
|----------|-----|-----|-----|-----|-----|
| x_3      | 0.8 | 0.5 | 0.8 | 0.5 | 0.5 |

Table 10: A comparison of the preference orders of the alternatives for different methods.

| Decision approach               | Reference | Preference order |
|---------------------------------|-----------|-----------------|
| Olusayo Obajemu et al.'s method | [12]      | x_3 > x_2 > x_1 |
| Daniel Sánchez method           | [14]      | x_2 > x_3 > x_1 |
| Jesús Alcalá-Fdez et al.'s method | [15]    | x_2 > x_3 > x_1 |
| Proposed method                  |           | x_2 > x_3 > x_1 |

We can see from above that the solution is precise and rational.

4. An Approach to Fuzzy Soft Set-Based Cluster-based Decision-Making

As we all know, weights of experts are critical in integrating independent, fleeting soft sets into a cluster-based standard collection. The authors found a complete similitude and proximity degree in [23] and used the weight limits control parameter. In [24] the writers try an important way to reduce the differences between the participant wishes and the cluster perspective and to take into account the varied expertise, experiences and interests of different decision-makers. In [25] the authors built a model for optimizing the cluster's consensus to draw the decision-makers' weight.

In [32], the authors suggested a way to maximize consensus on the weight of intuitive decision-making in the clusters. On this basis, we develop a new approach for assessing the weight of cluster-based experts. Experts are typically from various study areas in the practical cluster-based assessment phase and each specialist has its own understanding, qualifications and practical expertise. Such features are known to you, but not others. So, they know. In other words, the proof submitted by experts is largely lacking and the opinions of experts diverge. In [32], the authors suggested a way to maximize consensus on the weight of intuitive decision-making in the clusters. On this basis, we develop a new approach for assessing the weight of cluster-based experts.

Experts are usually from different fields of research during the functional cluster-based evaluation process and the experts have their own knowledge, skills and experience. Such features are known to you, but not others. So, they know. In other words, there is a significant lack of evidence from experts, and there are differences between experts. Therefore, we look at the question of joint decisions from the point of view of the cluster and the Member's point of view. In other words, we understand not only how the individual professional and society are continuing, but also how the decision-maker as an individual expert can gain useful experience.

4.1. Method Based on the Measurement of Knowledge of Fuzzy Soft Set for the Determination of Expert Weights.

The weight of experts is normally a significant factor in deciding the final decisions and should be thoroughly taken into account in the realistic multiexpert cluster-based decision-making process. In general, the latest methods to measuring expert weights are largely dependent on each expert's association with other experts or the ideal expert. Few ways of achieving the weight of the specialist
are suggested by understanding the uncertainty of the expert’s expertise with the decision-maker. In this paragraph, however, we suggest measuring the level of fuzziness of the soft fluid bundle. This paragraph contains data. Then, with the proposed knowledge measure, we develop a method of gathering suitable expert weights. In other words, from the point of view of the citizen the weights of experts may be gathered.

Definition 4.1.1. Let $F, E$ be a fuzzy soft set over $U$, the knowledge measure is defined as
\[
K(F, E) = \frac{1}{nm} \sum_{i=1}^{m} \sum_{j=1}^{n} (F(x)|x|)^2 + (1 - F(x)|x|)^2
\]

(10)
The data provided can easily be used to perform the tasks below. The thinner the field consciousness, the more detail is fluttered, the more these characteristics indicate. As the expert assessment of the expert’s flowy softness improves, the decision-making process based on a multi-expert cluster will provide decision makers with more valuable knowledge, such that the expert plays a relatively important role in the decisions based on the cluster process. A higher weight should be assigned to the professionals. Otherwise, a lot of lawmakers would consider such an expert as insignificant. A specialist like this should be given a lesser weight. It is suspected that the P specialists and the value of fuzzy soft sets are assessed, respectively $(Fk, E2)$ (alternatively $k - p$). (Alternatively). We will obtain the following weight of the expert $k$:
\[
\lambda_k = \frac{K(F_k, E)}{\sum_{k=1}^{P} K(F_k, E)}
\]

(11)

4.2. Method Based on the Divergence Degree for the Calculation of Expert Weights.

In furious soft sets, flexible and agile $\alpha$-similarity relationships are used to resolve cluster dependent decisions. As was explained in [24, 25, 33], the theory of the degree of divisiveness dependent on 5-007-similarity relationships is proposed first of all in order to avoid expert’s weights, to measure the differences between individual preferences and the point of view of populations.

Definition 4.2.1. Let $(F, E)$ be a soft fuzzy set over $U$, $A$ to $E$ and $\alpha$ to 0, 1 to be described as the $\alpha$-similarity relationship over a fluoridated soft set $(F, E)$ as
\[
(S^\alpha_A) = \{ (x, y) \in U \times U \mid \frac{F(e_i)(x)}{F(e_i)(x)} \cap \frac{F(e_i)(y)}{F(e_i)(y)} \geq \alpha, \forall e_i \in A \}
\]

(12)

It can be observed from this definition that if a couple of objects $x, y$ from $(U = U)$ belong to $SA \alpha$, they are considered equal. The relationship between $\alpha$-similarity is simple to assess but not necessarily transitive.

Let $F, E$ be an uncompromising soft-type range over $U$, for $x$ — for $U$ — for $A$ — for $E$ — for objects $x \alpha$ — for object $A$
\[
([x]_A^\alpha) = \{ y \in U \mid (y, x) \in (S^\alpha_A) \}
\]

(13)
The $\alpha$-similarity relationship under expert $k$ can be defined in terms of multi-expert team decision-making problems
\[
(S^k_A) = \{ (x, y) \in U \times U \mid \frac{F_k(e_i)(x)}{F_k(e_i)(x)} \cap \frac{F_k(e_i)(y)}{F_k(e_i)(y)} \geq \alpha, \forall e_i \in A \}
\]

(14)

Subsequently, subject $x$ about $A$ within specialist $k$ may be defined as the $\alpha$-similarity class based on
\[
([x]_A^k) = \{ y \in U \mid (y, x) \in (S^k_A) \}
\]

(15)
The cluster-based set of the class $\alpha$-similarity for choice $U$ of variable set $A$ can thus be expressed as follows under specialist $k$:
\[
\frac{0}{(S^\alpha_A)} = \{ ([x]_A^k)^\alpha \mid x \in U \}
\]

(16)

In the preceding, for all the options in the Set $A$ specification, we apply the concept of the degree of difference between experts $k$ and $l$.
\[
D_{kl} = \frac{1}{|U|} \sum_{x \in U} |[x]_A^k| - |[x]_A| - |[x]_A^k \cap [x]_A|= k, l \in P
\]

(17)

Equation (17) Represents the degree of divergence between two experts for all parameters set $A$ alternatives. The $(0 - Dkl)$ die $1$ $(1/ U)$ is easy to check. The narrower the DK, the poorer the discrepancy. The larger the Dkl, the closer the experts are K and L. In addition, the above notion of divergence is simple to see, as it excludes the use of the feature distance or similarity to quantify
difference in decision making and thus reduces the effect of many distinct functions of distance or uniqueness in the measurement of differentiation between clusters. Then (17) shows us how experts k and all other experts can be diverged \( l = 1, 2, \ldots, P, l \neq k \) as:

\[
M_k = \sum_{l=1, l \neq k}^P D_{kl} \quad P \quad l = \sum_{l=1}^P M_k \quad l = k
\]

(18)

Based on these evaluations, the specialist knows how to assess the weight of an expert should use a clear and accurate formula:

\[
\lambda_k^{(2)} = \frac{M_k^1}{\sum_{k=1}^P M_k^1}
\]

(19)

The attitude of decision-making makers as follows (20) for evaluating expert weights in group decisions based on fluid soft sets can be (11) and (19) integrated in reality along with the attitude. The ultimate weight of the expert k can be obtained by adding, \( \mu_k \)-1.

\[
\lambda_k = \rho \lambda_k^{(1)} + (1 - \rho) \lambda_k^{(2)} \quad (k = 1, 2, \ldots, P),
\]

(20)

Where \( \rho \) is the parameter which represent the decision-makers' attitudinal characteristics. Finally, we might create a multi-expert group-oriented algorithm to work with unknown expert weights in decision-making.

**Algorithm 2 (cluster-based decision-making based on fuzzy soft sets).**

**Input:** The fuzzy soft sets \( F_k, A \quad 1 \leq k \leq P \) over a finite initial universe \( U \) and a finite parameter set \( A \).

**Output:** The relationship between all alternatives.

**Step 1.** The measurements of information for all human soft fuzzy sets \( F_k, E \) of \( k = 1, 2, \ldots, P \), and then receive the weighting vector of the experts \( \lambda_1 = \lambda_1, \ldots, \lambda_1 \).

**Step 2.** Set the magnitude of the \( \lambda \) and calculate the extent to which the experts and the other experts differ, and guarantee, after that, that the vector vector weighting of the expert's vector \( \lambda_2 = \lambda_2 \) (19).

**Step 3.** Sets the value of \( S \), and let \( \mu = \beta_1, \beta_2, \ldots, \beta_P \) be the last 17 expert weights that can be established into this weighting vector (20).

**Step 4.** Calculate the built-in F, E by F F (5).

**Step 5.** Apply Algorithm 1 to the built-in Fuzzy soft set (F,E) and get better solutions.

5. **Comparison Analysis**

In this section the efficiency, viability, and effectiveness of the proposed method are illustrated and comparatively analysed.

5.1. **Illustrative Example.** This section presents a revised description from [32] to explain that the suggested approach is being employed to resolve a cluster-based decision-making problem based on fluid soft sets.

**Example 5.1.** Assume that 4 shortlisted candidates are considered for a spot by a corporation \( U = x_1, x_2, x_3, x_4 \). There will be an interview session where 3 researchers will examine each candidate in four ways: good behaviour \( e_1 \), friendliness \( e_2 \), good order \( e_3 \), and communication skills \( e_4 \). The set of parameters is \( E = e_1, e_2, e_3, e_4 \). Here, we say that the parameter vector is weighed as \( = e_1 = 1, = e_2 = 2, = e_3 = 2, = e_4 = 0 \). Weighting parameter vectors Here we assume that The weight of the experts is not understood. \( F_k, E k = 1,2,3 \) is an expert k soft package (Tables 11–13).

Then we take the methodology we have built to get an alternate ranking.

(1) Calculate the soft-set fluid measurement \( F_k, E \) \( k = 1,2,3 \).

As defined in 4.1.1, the measure \( K F_k, E k = 1,2,3 \) can be obtained as follows:

\[
K (F_1, E) = 0.7522,
K (F_2, E) = 0.7393,
K (F_3, E) = 0.7489.
\]

(21)

(2) Determine the specialist weights The experts will obtain the weighing vector as follows by using (11).

\[
\lambda_k^{(1)} = \lambda_k^{(1)}, \lambda_k^{(2)} = (0.3357,0.3300,0.3343).
\]

(22)
Let $\alpha = 0.6$ for the alternate set $U$ for parameters set $E$ to obtain the families set of the $\alpha$-similarity groups under expert $k = 1, 2, 3$.

The families of $\alpha$-similarity class $k = 1, 2, 3$ are available via (14), (15), and (16), as follows:

$$
U/(S^1_A)^\alpha = \{ x_1, x_2, x_3, x_4 \},
U/(S^2_A)^\alpha = \{ x_1, x_2, x_4 \},
U/(S^3_A)^\alpha = \{ x_1, x_3, x_4 \}.
$$

Table 11: The evaluation value of expert 1.

| $(F_1, E)$ | $e_1$ | $e_2$ | $e_3$ | $e_4$ |
|------------|-------|-------|-------|-------|
| $x_1$      | 0.6   | 0.7   | 0.5   | 0.8   |
| $x_2$      | 0.7   | 0.6   | 0.5   | 0.7   |
| $x_3$      | 0.4   | 0.9   | 0.6   | 0.7   |
| $x_4$      | 0.5   | 0.5   | 0.8   | 0.6   |

Table 12: The evaluation value of expert 2.

| $(F_2, E)$ | $e_1$ | $e_2$ | $e_3$ | $e_4$ |
|------------|-------|-------|-------|-------|
| $x_1$      | 0.5   | 0.7   | 0.6   | 0.6   |
| $x_2$      | 0.5   | 0.6   | 0.7   | 0.7   |
| $x_3$      | 0.6   | 0.3   | 0.5   | 0.8   |
| $x_4$      | 0.7   | 0.6   | 0.7   | 0.5   |

Table 13: The evaluation value of expert 3.

| $(F_3, E)$ | $e_1$ | $e_2$ | $e_3$ | $e_4$ |
|------------|-------|-------|-------|-------|
| $x_1$      | 0.6   | 0.7   | 0.6   | 0.5   |
| $x_2$      | 0.7   | 0.4   | 0.7   | 0.8   |
| $x_3$      | 0.7   | 0.6   | 0.6   | 0.5   |
| $x_4$      | 0.8   | 0.4   | 0.8   | 0.6   |

(4) Calculate the extent to which the two practitioners differ.

The degree of discrepancies can be calculated according to (17) on the basis of the $\alpha$-similarity class of the two experts: $D_{12} = 0.13$, $D_{13} = 0.5$, $D_{23} = 0.63$. (24)

(5) Get the professional weights. The experts will acquire the following calculation vectors using (18) and (19): $\mu(2) = \alpha(2), \beta(4), \text{"superstructure of the body" surgery" superior" subsequent"}$ (0.42, 0.35, 0.23). (25)

(6) Determine the final vector of weight of experts and set $\beta = 0.5$. Under (20), experts will acquire the final weight vector as follows: $\mu = (\beta_1, \mu_2, \mu_3) = (\text{zero-zero-zone}) \beta \mu (0.38, 0.34, 0.28)$ (26).

(7) The built in fuzzy soft collection is calculated. By means of (5) the total person flush soft set $(F_k, E_k) = 1, 2, 3$ can be added to obtain the integrated fluffy soft set $(F, E, Table 14)$. (27)

(8) The solutions are classified. With the use of algorithm 1, you can obtain the following rankings of all options $x_i = 1, 2, 3, 4$: Therefore, $x_3 = \text{percent } x_2 — \text{percent } x_1 = \text{percent } x_4$ is the optimal solution.

5.2. Sensitivity Measurement of the parameters.

In the above case, the equation results will be achieved in (14) and (20) respectively by setting a priori parameters. The various kinds usually $a_{jk} = \min \{ F_k(e_i) (x_j) \land F_k(e_i) (y_j) / F_k(e_i) (x_j) \lor F_k(e_i) (y_j) | j = 1, 2, ..., j \}$. 


\[ |U|, k = 1, 2, \ldots, P, e \in E, x_i \neq y_j \}, \quad (28) \]
\[ a = \min \{ a_{jk} | j = 1, 2, \ldots, |U|, k = 1, 2, \ldots, P \}, \]
\[ b = \max \{ a_{jk} | j = 1, 2, \ldots, |U|, k = 1, 2, \ldots, P \}. \]

(24)

Table 14: Collective fuzzy soft set.

| \((F, E)\) | \(e_1\) | \(e_2\) | \(e_3\) | \(e_4\) |
|---|---|---|---|---|
| \(x_1\) | 0.57 | 0.70 | 0.56 | 0.67 |
| \(x_2\) | 0.64 | 0.55 | 0.64 | 0.73 |
| \(x_3\) | 0.57 | 0.71 | 0.57 | 0.70 |
| \(x_4\) | 0.68 | 0.51 | 0.77 | 0.57 |

We have the \(\alpha\)-to, the \(\beta\)-to, where the \(\alpha\)-to-and-P is the number, and the E are the parameter range. The difference between two experts is 0 while \(\alpha\) – all the same. The difference between two specialists is 0. Thus, policy makers should choose the appropriate \(\alpha\) parameter depending on the realistic situation. Table 15 shows that the weights of experts differ with sensitive parameters \(\alpha\) and \(\bar{S}\). If the attitude of the policy makers is not changed, we will see it as the powers of experts shift.

The weight of the experts for the different values of the \(\mu\) parameters is not the same when the Parameter \(\alpha\) is constant. In other words, each expert's weight varies depending on the value of each parameter. It is also noted that, regarding different values of \(\alpha\) and \(\bar{S}\) parameters, the results of the classification may not be identical. According to the analysis above, this document allows decision-makers to provide clear insight on their goals through decision making by collaborative decision-making methodologies. In other words, by choosing suitable criteria, the strategy suggested would achieve the appropriate ranking results in accordance with the views of decision makers. The suggested compromise could also inspire policymakers to choose more.

Parameter values are accompanied by different rank orders, leading to various expert weights. In order to inspect the influence of the different parameters on the weights of the experts, sensitivity analysis of the parameters is needed. We can see from Example 5.1 that, whether \(\alpha = 0.43\) or \(\alpha = 0.86\), the difference is 0, but this is negligible, for any two experts. Decision-makers will need to know the 5-007 parameter scale. Overcome the mutual decision-making challenges and thereby increase harmony and durability.

5.3. Comparison with current approaches to extract expert weights.

We do a comparison analysis with another solution to prove the advantage of our proposed approach to calculating expert weight. Table 16 lists comprehensive comparisons of strategies [23–25, 27, 30]. We should finish the following, as seen in Table 16.

The method suggested is based on the degree of discrepancy and knowledge measurement in comparison with the Xiuqin Ma et al. method [27]. Instead, Xiuqin Ma et al's solution is dependent on distance. Given the accuracy of the expert and the society, Xiuqin Ma et al. receive the expert's weight by means of the distance. However, different functions of distance lead to different results. We propose an idea of the degree of divergence in calculating the weights of experts to prevent distance functions being used in determining the weight of experts. We also take into account the weights of the participant's experts. In other words, by looking at the flow of knowledge provided by the real expert, we can achieve the weights of the expert so that we can use an expert evaluation to determine the weights of the experts. The proposed method would then more objectively assess the weights of the experts. Our methodology is focused on the extent and extent of divergence compared to methods [24, 25, 30], and on the degree of consensus based upon the methods in [25, 25, 30].

Table 15: Experts’ weights and ranking results with different parameters \(\alpha\) and \(\rho\).
Parameters | Expert weights | Ranking results | Optimal
---|---|---|---
\(\alpha = 0.60\) | \(\rho = 0.3\) | \(0.40, 0.34, 0.26\) | \(x_3 \succ x_2 \succ x_1 \succ x_4\) | \(x_3\)
 | \(\rho = 0.5\) | \(0.38, 0.34, 0.28\) | \(x_3 \succ x_2 \succ x_1 \succ x_4\) | \(x_3\)
 | \(\rho = 0.8\) | \(0.35, 0.33, 0.31\) | \(x_2 \succ x_3 \succ x_1 \succ x_4\) | \(x_2\)

\(\alpha = 0.65\) | \(\rho = 0.3\) | \(0.36, 0.32, 0.32\) | \(x_2 \succ x_3 \succ x_1 \succ x_4\) | \(x_2\)
 | \(\rho = 0.5\) | \(0.35, 0.32, 0.33\) | \(x_2 \succ x_3 \succ x_1 \succ x_4\) | \(x_2\)
 | \(\rho = 0.8\) | \(0.34, 0.33, 0.33\) | \(x_3 \succ x_2 \succ x_1 \succ x_4\) | \(x_3\)

\(\alpha = 0.70\) | \(\rho = 0.3\) | \(0.35, 0.35, 0.30\) | \(x_2 \succ x_3 \succ x_1 \succ x_4\) | \(x_2\)
 | \(\rho = 0.5\) | \(0.34, 0.34, 0.31\) | \(x_2 \succ x_3 \succ x_1 \succ x_4\) | \(x_2\)
 | \(\rho = 0.8\) | \(0.34, 0.33, 0.33\) | \(x_3 \succ x_2 \succ x_1 \succ x_4\) | \(x_2\)

\(\alpha = 0.80\) | \(\rho = 0.3\) | \(0.38, 0.38, 0.24\) | \(x_2 \succ x_3 \succ x_1 \succ x_4\) | \(x_2\)
 | \(\rho = 0.5\) | \(0.37, 0.37, 0.27\) | \(x_3 \succ x_2 \succ x_1 \succ x_4\) | \(x_3\)
 | \(\rho = 0.8\) | \(0.35, 0.34, 0.31\) | \(x_3 \succ x_2 \succ x_1 \succ x_4\) | \(x_2\)

Table 16: Comparison with other existing methods for deriving the experts’ weights.

| Method | Measurement tool | The final results |
|---|---|---|
| The method in [27] | Distance | The consistency between the individual expert and the cluster-based |
| Methods in [24, 25, 30] | Consensus degree | The consistency between the individual expert and the cluster-based |
| The method in [23] | Distance | Similarity |
| | | Proximity |
| Proposed method | Divergence degree | The consistency between the individual expert and the cluster-based |
| | Knowledge measure | The fuzziness of the information provided by the individual expert |

In [24, 25, 30] the authors just assume the precision of the actual expert and the society in determining the experts’ weight; they do not regard the vacuity of the expert expertise. In order to more objectively assess any specialist, we are looking at the subject not just from the Party’s point of view, but also from the participant’s point of view. In other words, it is not just the consistency of the individual specialist with the society that we understand but also how important information can be provided as an individual professional to policy makers. This paper also provides a method more appropriate for the measurement of expert weights.

The weights of experts are determined by similarities and proximity, according to the system in [23], whereby the level of similitude in [23] is the predictor of knowledge in our method. The degree of closeness defined in [23] by distance is similar to that of our scheme. However, various distance
functions can produce different results. We propose the notion of the degree of divergence for calculating expert weights to avoid using distance functions to determine the weights of experts. The previous analysis shows that it is reasonable and correct to approach the decision on the weights of the experts. The experts’ weights can be evaluated more reliably. In addition, by changing the parameters (see (14) and (20)), weights of experts can be adjusted to allow decision-makers to deal more coherently with joint decision-making issues. 5.4. Process comparison at [32]. The methodology introduced in this paper contrasts in this subsection with another approach proposed for justifying supremacy of the proposed method by Krzysztof Trawiński [32]. Table 17 provides a thorough reference to the procedure in [32].

The ranking of alternate approaches obtained in Table 17 cannot be seen to be identical to that obtained by Krzysztof Trawiński. The central reason for the contradictory findings is that the methods used in the solution suggested to gain the weights of experts are different [32]. The method [32] just acknowledges the consistency of the expert and the collective and does not have the flexibility to know the decision-maker provided by the actual expert. In order to more scientifically derive the weight of each expert, the approach proposed examines not just how close the opinion of the expert is to others, but also how helpful it is to include information as specialists in the process of Group decision making for the decision-makers. We also apply a degree of calculation and divergence among the two experts on the basis of the similarities between the two experts in order to obtain the experts. Krzysztof Trawiński proposed a scheme on the basis of [32].

| Method | Measurement tool | Parameters | Experts’ weights | Ranking results |
|--------|-----------------|------------|------------------|-----------------|
| Proposed method | Divergence degree and knowledge measure | \(\alpha = 0.60, \rho = 0.3\) | \{0.39, 0.34, 0.26\} | \(x_3 \succ x_2 \succ x_1 \succ x_4\) |
| | | \(\alpha = 0.60, \rho = 0.5\) | \{0.38, 0.34, 0.28\} | \(x_3 \succ x_2 \succ x_1 \succ x_4\) |
| | | \(\alpha = 0.60, \rho = 0.8\) | \{0.35, 0.33, 0.31\} | \(x_2 \succ x_3 \succ x_1 \succ x_4\) |
| | | \(\alpha = 0.65, \rho = 0.3\) | \{0.36, 0.32, 0.32\} | \(x_2 \succ x_3 \succ x_1 \succ x_4\) |
| | | \(\alpha = 0.65, \rho = 0.5\) | \{0.35, 0.32, 0.33\} | \(x_2 \succ x_3 \succ x_1 \succ x_4\) |
| | | \(\alpha = 0.65, \rho = 0.8\) | \{0.34, 0.33, 0.33\} | \(x_2 \succ x_3 \succ x_1 \succ x_4\) |
| | | \(\alpha = 0.70, \rho = 0.3\) | \{0.35, 0.35, 0.30\} | \(x_3 \succ x_2 \succ x_1 \succ x_4\) |
| | | \(\alpha = 0.70, \rho = 0.5\) | \{0.34, 0.34, 0.31\} | \(x_2 \succ x_3 \succ x_1 \succ x_4\) |
| | | \(\alpha = 0.70, \rho = 0.8\) | \{0.34, 0.33, 0.33\} | \(x_2 \succ x_3 \succ x_1 \succ x_4\) |
| | | \(\alpha = 0.80, \rho = 0.3\) | \{0.38, 0.38, 0.24\} | \(x_2 \succ x_3 \succ x_1 \succ x_4\) |
| | | \(\alpha = 0.80, \rho = 0.5\) | \{0.37, 0.36, 0.27\} | \(x_3 \succ x_2 \succ x_1 \succ x_4\) |
| | | \(\alpha = 0.80, \rho = 0.8\) | \{0.35, 0.34, 0.31\} | \(x_2 \succ x_3 \succ x_1 \succ x_4\) |
| Method [32] | Similarity measure | \(\alpha = 0.50\) | \{0.33, 0.33, 0.34\} | \(x_4 \succ x_2 \succ x_1 \succ x_3\) |

Similarity tests in multi-expert group decision making for expert weight evaluation. But different functions of similarities will produce different results. We use the notion of a divergence degree to gather the weights of the experts to avoid using similarity functions to decide their weights. The meaning is simple and logical. It is easy to understand. Compared with the methodology proposed by [32] in the ranking of alternatives in section 3, \(x_2 \succ x_1 \succ x_3 \succ x_4\) is ranked. Table 15 shows that the results of the decision-making phase in the ranking are different [32]. An additional clarification of different ranking results is also provided by the various decisions developed in our methodology and [32]. The former uses the implied interval between two fuzzy soft sets, which classifies alternatives according to the score indices. The latter calculates the alternatives. This document has lower costs for the calculation of the decision-making process than those in [32].
While different parameter values can lead to different order of rating, Table 17 shows that there may be
\( x_2 = x_3 \text{ umo} = x_3 \text{ umo} x_4 \) or \( x_3 \text{ - alternatives} = x_2 \text{ umo} x_2 \text{ umo} x_4 = x_2 \text{ umo} - x_4 \). However, how can we decide which order of ranking is the desired order? We notice that \( x_2/to x_3/1x/to/to x_3/tox2/1x/tox2/tox4 \) is given four times in Table 17, so we can select the order of ranking according to the frequency at which they occur. Thus, \( x_2/tox3/1x/tox4 \) is most probably the order of ranking you want to rank. So, when we choose \( x_2 \) as the ideal object it will have little chance.

We know that different parameter values will give ranking of alternatives in different orders because of algorithm 2's parameters \( \alpha, \beta \) and 2. We can then perform repeated experiments by choosing the parameters of \( \alpha, \mu \), randomly on Algorithm 2, leading to a ranking of multiple results that count the incidence times, and the order of the ranking among all rank orders, which is the best order of all ranking orders replicated. Our proposed approach has some benefits compared to Krzysztof Trawiński [32]:

1. The proposed approach shall be able to solve the position of many experts, subjectivity and imprecision within the Community multi-expert policy dilemma.
2. Technologies used would measure the weights of the experts statistically and thus eliminate the arbitrary randomness of weight calculations.
3. The weights of experts should be changed to allow further flexibility for decision makers in the selection of an order of classification most likely to be an appropriate order of classification.

6. Conclusion
In this essay we propose to address the issue of soft-set decisions by introducing a new, distance-based solution. The concepts of the knowledge estimate and the extent of divergence are applied to measure each expert's weight objectively. We develop two approaches to the necessary expert weights based on the principles. In conjunction of the two systems, the final weights of the experts are achieved. Then, by integrating the approaches we embody, we create an effective approach to group decision making. Finally, the approaches used to clarify the suggested solution and to compare it with other existing methods, are presented as an illustration and sensitivity analysis. This highlights the reasoning and utility of the modern decision-making process discussed in our paper.

Further analysis may be required if the existing approaches are to be extended to other practical policy environments, such as the abstract, intuitive world.

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