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Application of Average fs-Aggregate Algorithm for Multi-criteria Decision Making in Real Life Problem

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Author's contribution

The sole author designed, analysed, interpreted and prepared the manuscript.

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Case Study

Abstract

Generally in our day to day life we come across the real life situations when right decision making becomes difficult. In different fields like economics, social science, medical science, environment, where such complicacy arises and involves uncertainties. The conventional mathematical methods are unsuitable to solve such problems. To solve this problem, we are to find the various parameters related to the problem to use them to get the accurate result. So fuzzy soft set theory is the best mathematical tool for solving such problems using different techniques. In this research paper, we have taken a multi-criteria real life problem to select a suitable city which suits the best conditions as per the given parameters. For getting the solution, we used average fs-aggregation algorithm for using multi-criteria parameters.

Keywords: Fuzzy set; fuzzy soft set; average fs-aggregate.

1 Introduction

In the fields of engineering, economics, social science, medical science, environment, etc. many complicated problems arise "involving uncertainties, classical methods are found to be inadequate in recent times". To deal with this uncertainty, in 1965 Zadeh [1] developed the theory of fuzzy sets. Molodtsov [2] pointed out

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that existing theories, namely Probability Theory, Intuitionistic Fuzzy Set Theory, Fuzzy Set Theory, Rough Set Theory etc. have their own limitations for solving problems regarding uncertainties. He also explained that there are some limitation for solution due to the inadequacy of the parameterization tool of the fuzzy set theory, as such problems have multi-criteria in attributes. He initiated the novel concept of Soft Set in 1999 as a new mathematical tool to deal with this problem. This soft set theory can be merged with previous theories. Scholars have proposed Probabilistic soft sets (Fatimah et al. [3]), Fuzzy soft sets (Maji et al. [4]), etc.

This new soft set theory found to be very useful in different fields using different techniques and showed great success. Molodtsov [2,5,6,7] applied this theory with different techniques formulating as the notions of soft number, soft integral and soft derivative etc. Maji et al. [8,9] studied it in detail and applied in decision making problems. Pawlak [10] proposed the reduction of rough sets, while Kong et al. [11] presented the normal parameterization reduction of soft sets and Chen et al. [12] gave parameterization reduction of soft sets. Zhan et al. [13] did a comprehensive study of that problem.

To obtain a better result in a more justified manner, many researchers used parameters through a different mathematical approach. Xiao et al. [14] formulated synthetic evaluation method, and gave a recognition for soft information based on the theory of soft sets [15]. Mushrif et al. [16] developed the algorithm based on the notions of soft set theory. Pei and Miao [17] worked on the soft sets to show a class of special information system, while Zou and Xiao [18] presented data analysis approaches of soft sets. Kovkov et al. [19] worked on optimization problems, whereas Majumdar and Samanta [20] worked on the similarity of soft sets and Ali et al. [21] presented a few new operations in soft set theory.

Many scholars around the globe presented their work with different novel concepts in interesting way to obtain more accurate result. Maji et al. [4] presented the concept of fuzzy soft sets by embedding the idea of fuzzy sets, whereas Roy and Maji [22] presented a different application of fs sets. Som [23] defined fuzzy soft relations and soft set relations. Krishna Gogoi et al. [24] worked on fuzzy soft set and Bhardwaj et al. [25] used Reduct soft set for real life decision making problems. Alcantud et al. [26] presented a concept of Partial Valuation Fuzzy Soft Set (PVFSS) and introduced the application of data filling in PVFSS. Irkin [27] generated the sensory score and presented a fuzzy soft set modeling in his study to find the maximum score. Kalaichelavi et al. [28], Karaca and Tas [29] presented notions of soft set and fuzzy soft sets. Ozgur and Tas [30] introduce a new method to include the notion of period using soft set and matrix form theories for solving investment decision making problem. Tas et al. [31] applied soft set theory and fuzzy soft set theory for the effective measurement of stock-out situations.

Maji et al. [4,9] defined the fundamental definitions of soft sets and fs sets which are used as an important basic operation. But Chen et al. [12], Pei and Miao [17], Kong et al. [32] and Ali et al. [21] pointed out some weak points of earlier work. Cogman and Enginoglu [33] redefined the operations of soft sets to develop the theory which became more functional for improving the approach and results. Cogman and Enginoglu [34] later came up with a soft matrix theory. Cagman et al. [35] defined a fuzzy parameterized soft set theory and its application.

In this paper author is defining fuzzy soft set and applying **average fuzzy soft set aggregation algorithm** to solve decision making problems. The fs-aggregation algorithm is well defined by Cagman et al. [36] for decision making. We extended the present algorithm for multi-criteria parameters and then successfully applied for the problem of real life containing uncertainties**. The given example and result obtained show that extended algorithm work well when we have multiple layers of parameters obtained through different sources.**

2 Preliminaries

In this section, we present the basic definitions of fuzzy set theory [1] and soft set theory [2] that are useful for subsequent discussions. Throughout this work, U refers to an initial universe, E is a set of parameters, P(U) is the power set of U, and $A \subseteq E$.

Let us recall the notation of Fuzzy Set as follows:

2.1. Let U be a universe. A fuzzy set X over U is a set defined by a function μ_X representing a mapping

μ_x: U → [0, 1]

μ_x is called the membership function of X, and the value μ_X (u) is called the grade of membership of u ∈ U. The value represents the degree of u belonging to the fuzzy set X. Thus, a fuzzy set X over U can be represented as follows:

X = {(μ_X (u)/u), u ∈ U, μ_X (x) ∈ [0, 1]}.

The set of all the fuzzy sets over U will be denoted by F(U).

2.2. A soft set F_A over U is a set defined by a function f_A representing a mapping

f_A : E → P (U) such that $f_A(x) = Ø$; if x∉ A

Here, f_A is called approximate function of the soft set F_A, and the value $f_A(x)$ is a set called x-element of the soft set for all x∈E. The sets $f_A(x)$ may be empty, arbitrary or have nonempty intersection. Thus a soft set over U can be represented by the set of ordered pairs

F_A = {(x, $f_A(x)$) : x ∈ E, $f_A(x)$ ∈ P (U)}

the set of all soft sets over U will be denoted by S(U).

Example: Let U = {u_l, u_2, u_3, u_4, u_5} be a universal set and E = {x_1, x_2, x_3, x_4} be a set of parameters. If A = {x_1, x_2, x_4} ⊆E, $f_A(x_1)$ = {u_2, u_4}, $f_A(x_2)$ = U and $f_A(x_4)$ = {u_1, u_3, u_5}, then the soft set F_A is written by

F_A = {(x_1, {u_2, u_4}), (x_2, U), (x_4, {u_1, u_3, u_5})}.

In the soft sets, the approximate functions and the parameter sets are crisp. But in the fs-sets, while the parameters sets are crisp, the approximate functions are fuzzy subsets of U. From now on, we will use Γ_A, Γ_B, Γ_C ,..., etc. for fs-sets and γ_A, γ_B, γ_C, etc. for their fuzzy approximate functions, respectively.

2.3. An fs-set Γ_A over U is a set defined by a function γ_A representing a mapping

γ_A: E → F (U) such that $\gamma_A(x) = Ø$; if x ∉ A:

Here, γ_A is called fuzzy approximate function of the fs-set Γ_A, and the value $\gamma_A(x)$ is a set called x-element of the fs-set for all x€ E. Thus, an fs-set Γ_A over U can be represented by the set of ordered pairs

$\Gamma_{A=}$ {(x, $\gamma_A(x)$) : x ∈ E; $\gamma_A(x)$ ∈ F(U)}:

Note that the set of all fs-sets over U will be denoted by FS(U).

Example. Let U = {u_l, u_2, u_3, u_4, u_5} be a universal set and E = {x_1, x_2, x_3, x_4} be a set of parameters. If A = {x_1, x_2, x_4}⊆ E, $\gamma_A(x_1)$ = {0.9/u_2,

0.5/u_4}, $\gamma_A(x_2)$ = U, and $\gamma_A(x_4)$ = {0.2/u_1, 0.4/u_3, 0.8/u_5} then the soft set F_A is written by

F_A = {(x_1, {0.9/u_2, 0.5/u_4}), (x_2; U), (x_4, {0.2/u_1, 0.4/u_3,0.8/u_5})}.

2.4. Let $\Gamma_A \in FS(U)$. If $\gamma_A(x) = \emptyset$; for all $x \in E$, then Γ_A is called an empty fs-set, denoted by $\Gamma\Phi$.

2.5. Let $\Gamma_A \in FS(U)$. If $\gamma_A(x) = U$ for all $x \in A$, then Γ_A is called A-universal fs-set, denoted by $\Gamma\ \tilde{A}$.

If A = E, then the A-universal fs-set is called universal fs-set, denoted by $\Gamma\ \tilde{E}$.

Example. Assume that $U = \{u_1, u_2, u_3, u_4, u_5\}$ is a universal set and $E = \{x_1, x_2, x_3, x_4\}$ is a set of all parameters.

If $A = \{x_2, x_3, x_4\}$, $\gamma_A(x_2) = \{0.5/u_2, 0.9/u_4\}$, $\gamma_A(x_3) = \emptyset$; and $\gamma_A(x_4) = U$, then the fs-set Γ_A is written by $\Gamma_A = \{(x_2, \{0.5/u_2, 0.9/u_4\}), (x_4, U)\}$.

If $B = \{x_1, x_3\}$, and $\gamma_B(x_1) = \emptyset$, $\gamma_B(x_3) = \emptyset$, then the fs-set Γ_B is an empty fs-set, i.e. $\Gamma_B = \Gamma\Phi$.

If $C = \{x_1, x_2\}$, $\gamma_C(x_1) = U$, and $\gamma_C(x_2) = U$, then the fs-set Γ_C is a C-universal fs-set, i.e., $\Gamma C = \Gamma_C^{\sim}$.

If D = E, and $\gamma_D(x_i) = U$ for all $x_i \in E$, where i =1,2,3,4, then the fs-set Γ_D is a universal fs-set, i.e., $\Gamma D = \Gamma\ \tilde{E}$.

3 Average fs-Aggregation Algorithm

The present study introduces a new concept in which three different fs-sets are generated. Finally the study defines an average fs-aggregation operator which produces an aggregate fuzzy set from fs-sets and its cardinal set. The approximate functions of an fs-set are fuzzy. An fs-aggregation operator on the fuzzy sets is an operation by which several approximate functions of an fs-set are combined to produce a single fuzzy set which is the aggregate fuzzy set of the fs-set. Once an aggregate fuzzy set has been arrived at, it is necessary to choose the best single crisp alternative from this set.

Therefore,

Step 1: Construct different fs-sets ΓA_1, ΓA_2, ΓA_3 over U.
Step 2: Construct an average fs- set Γ_A over U.
Step 3. Find the cardinal set $c\Gamma_A$ of Γ_A.
Step 4: Find the aggregate fuzzy set Γ^*_A of Γ_A.
Step 5: Find the best alternative from this set that has the largest member-ship grade by max $\Gamma^*_A(u)$.

A. Step 1:

Let $\Gamma_A \in FS(U)$. Assume that $U = \{u_1; u_2; \ldots; u_m\}$, $E = \{x_1; x_2; \ldots; x_n\}$ and $A \subseteq E$, then different fs-sets ΓA_1, ΓA_2, $\Gamma A_{3\ldots}$ ΓA_n over U can be presented as per the following table.

ΓA_1	X_1	X_2	.	X_n
u_1	$\mu\gamma A(x_1)(u_1)$	$\mu\gamma A(x_2)(u_1)$	.	$\mu\gamma A(xn)(u_1)$
u_2	$\mu\gamma A(x_1)(u_2)$	$\mu\gamma A(x_2)(u_2)$	.	$\mu\gamma A(xn)(u_2)$
.	.	.	. .	
.	.	.	. .	
.	.	.		.
u_m	$\mu\gamma A(x_1)(u_m)$	$\mu\gamma A(x_2)(u_m)$	.	$\mu\gamma A(x_n)(u_m)$

Similarly we can generate ΓA_2 and $\Gamma A_{3\ldots\ldots}$ ΓA_n

B. Step 2:

So taking the average of the above all soft sets ΓA_1, ΓA_2, ΓA_3 ….. ΓA_n we get the performance fs-set ΓA over U

- Let $\Gamma_A \in FS(U)$. Assume that $U = \{u_1; u_2; \ldots; u_m\}$, $E = \{x_1; x_2; \ldots; x_n\}$ and $A \subseteq E$, then the Γ_A can be presented by the following table.

ΓA	X_1	X_2	.	X_n
u_1	$\mu\gamma A(x_1)(u_1)$	$\mu\gamma A(x_2)(u_1)$	.	$\mu\gamma A(xn)(u_1)$
u_2	$\mu\gamma A(x_1)(u_2)$	$\mu\gamma A(x_2)(u_2)$	.	$\mu\gamma A(xn)(u_2)$
.	.	.	. .	
.	.	.	. .	
.	.	.		.
u_m	$\mu\gamma A(x_1)(u_m)$	$\mu\gamma A(x_2)(u_m)$	.	$\mu\gamma A(x_n)(u_m)$

Where $a_{ij} = \mu\gamma A(x)$ is the membership function of ΓA. If $a_{ij} = \mu\gamma A(x_j)\ (u_i)$ for $i=1,2,\ldots.m$ and $j=1,2,\ldots n$ then the fs-set ΓA is uniquely characterised by the matrix

$$[aij]_{mxn} = \begin{bmatrix} a11 & a12 & \ldots. & a1n \\ a21 & a22 & \ldots & a2n \\ . & . & & . \\ . & . & \ddots & . \\ . & . & & . \\ am1 & am2 & \ldots & amn \end{bmatrix}$$

This matrix is called an m x n fs-matrix of the fs-set ΓA over U.

C. Step 3:

Let ΓA € FS(U) then the cardinal set ΓA denoted by cΓA and defined by $c\Gamma A=\{\mu c\Gamma A(x)/x : x \in E\}$ is a fuzzy set over E. The membership function μcΓA of cΓA is defined by

$$\mu c\Gamma_A : E \rightarrow [0,1],\ \mu c\Gamma_A(x) = \frac{|\gamma A(x)|}{|U|}$$

where $|U|$ is the cardinality of universe U.

And $|\gamma_A(x)|$ is the scalar cardinality of fuzzy set $\gamma_A(x)$. The set of all cardinal sets of the fs-sets over U will be denoted by $cFS(U) \subseteq F(E)$.

Now let $\Gamma A \in FS(U)$ and $c\Gamma A \in cFS(U)$. Assume that $E=\{x_1,x_2,\ldots..,x_n\}$ and $A \subseteq E$, then cΓA can be presented by the following table

E	x_1	x_2	……	x_n
μcΓA	$\mu c\Gamma A(x_1)$	$\mu c\Gamma A(x_2)$	……….	$\mu c\Gamma A(x_n)$

If $a_{1j} = \mu c\Gamma_A(xj)$ for $j=1,2,\ldots..n$, then the cardinal set $c\Gamma_A$ is uniquely characterised by a matrix,

$[a1j]_{1xn} = [a_{11}, a_{12}, \ldots\ a_{1n}]$

Which is called the cardinal matrix of the cardinal set $c\Gamma_A$ over E.

D. Step 4:

let ΓA ∈ FS(U) and cΓA ∈ cFS(U). then fs-aggregation operator, denoted by FSagg, is defined by

FSagg :cFS(U) x FS(U) →F(U), FSagg($c\Gamma_A$, Γ_A)= Γ^*_A

Where Γ^*_A ={ $\mu\Gamma^*_A(u)/u$:u€U} is a fuzzy set over U. Γ^*_A is called the aggregate fuzzy set of the fs-set Γ_A. The membership function $\mu\Gamma^*_A$ of Γ^*_A is denoted as follows:

$\mu\Gamma^*A$: U→[0,1] , $\mu\Gamma^*A(u)=\frac{1}{|E|}\sum_{x\in E}\mu c\Gamma A(x)\mu\gamma A(x)(u)$

where $|E|$ is the cardinality of E.

Now assume that U={u_1, u_2, …u_m}, then the Γ*A can be presented by the following table.

ΓA	μΓ*A
u1	μΓ*A(u1)
u2	μΓ*A(u2)
.	.
.	.
.	.
um	μΓ*A(um)

If a_{i1}= $\mu\Gamma^*_A$ (u_i) for i=1,2,….m then Γ*A is uniquely characterised by the matrix

$$[a_{i1}]m\times 1=\begin{bmatrix} a11 \\ a21 \\ . \\ . \\ . \\ am1 \end{bmatrix}$$

Which is called the aggregate matrix of Γ*A over U.

If MΓA, McΓA, MΓ*A are representation matrices of ΓA, cΓA and Γ*A, respectively then

$|E|$ x MΓ*A = MΓA x M^T ΓA

Then MΓ*A = $\frac{1}{|E|}$MΓA x M^T ΓA

Where M^T ΓA is the transposition of M ΓA and $|E|$ is the cardinality of E.

E. Step 5

Find the best alternative from this aggregate fuzzy set Γ*A that has the largest member-ship grade by max $\Gamma^*_A(u)$.

4 Application

A company wants to establish his new office in a state. The company gave the demand for the survey data based on various parameters of the cities in the state to the three different agencies viz. A_1. A_2 A_3. The set of alternatives of four cities in the state is U={ c_1,c_2,c_3,c_4}. The various parameters of the study of these cities are population of the city, distance from Airport & Railway Station, Available skilled man power in the city, Distance from the capital of the state and Crime rate in the city. They give different weights to the parameters in terms of fuzzy set to each city. Thus the set of parameters is E= {x_1,x_2,x_3,x_4,x_5}

where

$x_{1=}$ Population of the city
$x_{2=}$ Distance from Airport & Railway Station
$x_{3=}$, Available skilled man power in the city
$x_{4=}$, Distance from the capital of the state
$x_{5=}$ Crime rate in the city

Here we have applied fs-Aggregation algorithm for the study of different cities in the state for making right decision for establishing the new office in a best suitable city.

Step 1: The data provided by the Survey agencies forms the fuzzy soft sets ΓA_1, ΓA_2, ΓA_3 over U as fallow:

ΓA_1	x1	x2	x3	x4	x5
c_1	0.8	0.6	0.4	0.6	0.4
c_2	0.7	0.6	0.4	0.6	0.7
c_3	0.6	0.5	0.4	0.6	0.5
c_4	0.9	0.6	0.3	0.9	0.5

ΓA_2	x1	x2	x3	x4	x5
c_1	0.6	0.5	0.2	0.8	0.5
c_2	0.6	0.5	0.5	0.4	0.6
c_3	0.4	0.6	0.4	0.5	0.7
c_4	0.8	0.4	0.2	0.7	0.5

ΓA_3	x1	x2	x3	x4	x5
c_1	0.7	0.4	0.3	0.7	0.6
c_2	0.5	0.7	0.3	0.5	0.5
c_3	0.5	0.7	0.4	0.4	0.6
c_4	0.7	0.5	0.4	0.8	0.5

So taking the average of the above three soft sets ΓA_1, ΓA_2, ΓA_3 we get the performance fs-set ΓA over U.

Step 2.: Construct an fs-set ΓA over U as given in the following table

ΓA	x1	x2	x3	x4	x5
c_1	0.7	0.5	0.3	0.7	0.5
c_2	0.6	0.6	0.4	0.5	0.6
c_3	0.5	0.6	0.4	0.5	0.6
c_4	0.8	0.5	0.3	0.8	0.5

Then $[aij]_{mxn}$ is called an m x n fs-matrix of the

fs- set ΓA over U as given below.

$$[aij]mxn = \begin{bmatrix} 0.7 & 0.5 & 0.3 & 0.7 & 0.5 \\ 0.6 & 0.6 & 0.4 & 0.5 & 0.6 \\ 0.5 & 0.6 & 0.4 & 0.5 & 0.6 \\ 0.8 & 0.5 & 0.3 & 0.8 & 0.5 \end{bmatrix}$$

Step 3: The cardinal set cΓA of ΓA is computed as fallows:

μcΓa(x1) = (0.7+0.6+0.5+0.8)/4=0.65

μcΓa(x2) = (0.5+0.6+0.6+0.5+)/4=0.55

μcΓa(x3) = (0.3+0.4+0.4+0.3)/4=0.35

μcΓa(x4) = (0.7+0.5+0.5+0.8)/4=0.625

μcΓa(x5) = (0.5+0.6+0.6+0.5)/4=0.55

So cardinal set cΓA = {0.65/x_1, 0.55/x_2, 0.35/x_3, 0.625/x_4, 0.55/x_5}

Step 4: The aggregate fuzzy set MΓ*A is computed as follows:

$$M\Gamma^*A = 1/5 \begin{bmatrix} 0.7 & 0.5 & 0.3 & 0.7 & 0.5 \\ 0.6 & 0.6 & 0.4 & 0.5 & 0.6 \\ 0.5 & 0.6 & 0.4 & 0.5 & 0.6 \\ 0.8 & 0.5 & 0.3 & 0.8 & 0.5 \end{bmatrix} \begin{vmatrix} 0.65 \\ 0.55 \\ 0.35 \\ 0.625 \\ 0.55 \end{vmatrix} = \begin{vmatrix} 0.310 \\ 0.301 \\ 0.288 \\ 0.335 \end{vmatrix}$$

That means,

Γ*A ={0.310/c_1, 0.301/c_2, 0.288/c_3, 0.355/c_4}

Step 5: Finally the largest membership grade is chosen by max μΓ*A(u) = 0.355

Which means that that the city c_4 has the largest membership grade, hence c_4 is the best suitable city which has the parameters as x_1=0.8, x_2=0.5, x_3=0.3, x_4=0.8 and x_5=0.5. and we may also grading the cities on the basis on membership grade that c_4,c_1,c_2 and c_3 are in decreasing grade on the basis of given parameters.

5 Conclusion

Here in this paper for using average fs-aggregation method we first explained some basic concepts of fuzzy soft set theory and its operations. Here we have taken a multi-criteria real life problem to apply the extended application of fs-aggregation algorithm. We developed fs-aggregation algorithm in more simplified and precisely analytic than the existed methods for the application point of view. Finally, we explained the successful application and output of this method. Our aim is that we can apply the fs-aggregation algorithm for such extended problems which contains multi-criteria in the real life situations. The method can be extended to the recent model Fuzzy N-soft sets too. They are a natural generalization of Fuzzy soft sets by inspiration of N-soft sets. The references that introduce these two models are [37],[38-]. So the average fs-aggregation algorithm can be extended using different approaches for multiple layers of parameters in real life problems.

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Competing Interests

Author has declared that no competing interests exist.

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