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.

Article Information

DOI: 10.9734/AJPAS/2018/v2i228772

Editor(s):

(1) Dr. Belkacem Chaouchi, Professor, Department of Mathematics, Khemis Miliana University, Algeria.

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(3) José Carlos R. Alcantud, University of Salamanca, Spain.

Complete Peer review History: http://www.sciencedomain.org/review-history/27795

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 Xiao [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 Xiao [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 ⊆ 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 \( \mu_X \) representing a mapping \( \mu_X : U \rightarrow [0, 1] \).

\( \mu_X \) is called the membership function of X, and the value \( \mu_X(u) \) is called the grade of membership of \( u \in U \). 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:

\[
X = \{ (\mu_X(u)/u), u \in U, \mu_X(u) \in [0, 1] \}.
\]

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 \( f_A : E \rightarrow P(U) \) such that \( f_A(x) = \emptyset \) if \( x \notin A \).

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 \( x \in E \). 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 \( F_A = \{(x, f_A(x)): x \in E, f_A(x) \in P(U)\} \).

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

Example: Let U = \( \{u_1, u_2, u_3, u_4, u_5\} \) be a universal set and E = \( \{x_1, x_2, x_3, x_4\} \) be a set of parameters. If \( A = \{x_1, x_2, x_4\} \subseteq E \), \( f_A(x_1) = \{u_2, u_4\} \), \( f_A(x_2) = U \), and \( f_A(x_4) = \{0.2/u_1, 0.4/u_3, 0.8/u_5\} \), then the soft set \( F_A \) is written by \( F_A = \{(x_1, \{0.9/u_2, 0.5/u_4\}), (x_2, U), (x_4, \{0.2/u_1, 0.4/u_3, 0.8/u_5\})\} \).

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 \( \Gamma_A, \Gamma_B, \Gamma_C, \ldots \) etc. for fs-sets and \( \gamma_A, \gamma_B, \gamma_C, \ldots \) etc. for their fuzzy approximate functions, respectively.

2.3. An fs-set \( \Gamma_A \) over U is a set defined by a function \( \gamma_A \) representing a mapping \( \gamma_A : E \rightarrow F(U) \) such that \( \gamma_A(x) = \emptyset \) if \( x \notin A \).

Here, \( \gamma_A \) is called fuzzy approximate function of the fs-set \( \Gamma_A \) and the value \( \gamma_A(x) \) is a set called x-element of the fs-set for all \( x \in E \). Thus, an fs-set \( \Gamma_A \) over U can be represented by the set of ordered pairs \( \Gamma_A = \{(x, \gamma_A(x)) : x \in E, \gamma_A(x) \in F(U)\} \).

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

Example. Let U = \( \{u_1, u_2, u_3, u_4, u_5\} \) be a universal set and E = \( \{x_1, x_2, x_3, x_4\} \) be a set of parameters. If \( A = \{x_1, x_2, x_3\} \subseteq E \), \( \gamma_A(x_1) = \{0.9/u_2, 0.5/u_4\} \), \( \gamma_A(x_2) = U \), 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 $\Gamma_A \in \text{FS}(U)$. If $\gamma_A(x) = \emptyset$; for all $x \in E$, then $\Gamma_A$ is called an empty fs-set, denoted by $\Gamma \Phi$.

2.5. Let $\Gamma_A \in \text{FS}(U)$. If $\gamma_A(x) = U$ for all $x \in A$, then $\Gamma_A$ 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 $\Gamma$. 

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 $\Gamma_A$ 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 $\Gamma_B$ 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 $\Gamma_C$ is a C-universal fs-set, i.e., $\Gamma_C = \Gamma \tilde{C}$.

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 $\Gamma_D$ is a universal fs-set, i.e., $\Gamma_D = \Gamma$.

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 $\Gamma_A_1, \Gamma_A_2, \Gamma_A_3$ over U.
Step 2: Construct an average fs-set $\Gamma_A$ over U.
Step 3: Find the cardinal set $c\Gamma_A$ of $\Gamma_A$.
Step 4: Find the aggregate fuzzy set $\Gamma^*_A$ of $\Gamma_A$.
Step 5: Find the best alternative from this set that has the largest membership grade by $\max \Gamma^*_A(u)$.

A. Step 1:

Let $\Gamma_A \in \text{FS}(U)$. 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 $\Gamma_A$, $\Gamma_A_2, \Gamma_A_3, \ldots, \Gamma_A_n$ over U can be presented as per the following table.

<table>
<thead>
<tr>
<th>$\Gamma_A$</th>
<th>$X_1$</th>
<th>$X_2$</th>
<th>$X_3$</th>
<th>$X_n$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_1$</td>
<td>$\mu\gamma_A(x_1)(u_1)$</td>
<td>$\mu\gamma_A(x_2)(u_1)$</td>
<td>$\mu\gamma_A(x_3)(u_1)$</td>
<td></td>
</tr>
<tr>
<td>$u_2$</td>
<td>$\mu\gamma_A(x_1)(u_2)$</td>
<td>$\mu\gamma_A(x_2)(u_2)$</td>
<td>$\mu\gamma_A(x_3)(u_2)$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\mu\gamma_A(x_1)(u_3)$</td>
<td>$\mu\gamma_A(x_2)(u_3)$</td>
<td>$\mu\gamma_A(x_3)(u_3)$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\mu\gamma_A(x_1)(u_4)$</td>
<td>$\mu\gamma_A(x_2)(u_4)$</td>
<td>$\mu\gamma_A(x_3)(u_4)$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\mu\gamma_A(x_1)(u_m)$</td>
<td>$\mu\gamma_A(x_2)(u_m)$</td>
<td>$\mu\gamma_A(x_3)(u_m)$</td>
<td></td>
</tr>
</tbody>
</table>

Similarly we can generate $\Gamma_A_2$ and $\Gamma_A_3$..... $\Gamma_A_n$
B. Step 2:

So taking the average of the above all soft sets $\Gamma A_1$, $\Gamma A_2$, $\Gamma A_3$ .... $\Gamma A_n$ we get the performance fs-set $\Gamma A$ 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 $\Gamma A_\lambda$ can be presented by the following table.

<table>
<thead>
<tr>
<th>$\Gamma A$</th>
<th>$X_1$</th>
<th>$X_2$</th>
<th>$\ldots$</th>
<th>$X_n$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u_1$</td>
<td>$\mu \gamma A(x_1)(u_1)$</td>
<td>$\mu \gamma A(x_2)(u_1)$</td>
<td>$\ldots$</td>
<td>$\mu \gamma A(x_n)(u_1)$</td>
</tr>
<tr>
<td>$u_2$</td>
<td>$\mu \gamma A(x_1)(u_2)$</td>
<td>$\mu \gamma A(x_2)(u_2)$</td>
<td>$\ldots$</td>
<td>$\mu \gamma A(x_n)(u_2)$</td>
</tr>
<tr>
<td>$\ldots$</td>
<td>$\ldots$</td>
<td>$\ldots$</td>
<td>$\ldots$</td>
<td>$\ldots$</td>
</tr>
<tr>
<td>$u_m$</td>
<td>$\mu \gamma A(x_1)(u_m)$</td>
<td>$\mu \gamma A(x_2)(u_m)$</td>
<td>$\ldots$</td>
<td>$\mu \gamma A(x_n)(u_m)$</td>
</tr>
</tbody>
</table>

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

$$
[a_{ij}]_{m \times n} = \begin{bmatrix}
  a_{11} & a_{12} & \ldots & a_{1n} \\
  a_{21} & a_{22} & \ldots & a_{2n} \\
  \vdots & \vdots & \ddots & \vdots \\
  a_{m1} & a_{m2} & \ldots & a_{mn}
\end{bmatrix}
$$

This matrix is called an $m \times n$ fs-matrix of the fs-set $\Gamma A$ over $U$.

C. Step 3:

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

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

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 $c\Gamma A$ can be presented by the following table

$$
\begin{array}{c|cccc}
E & x_1 & x_2 & \ldots & x_n \\
\hline
\mu c\Gamma A & \mu c\Gamma A(x_1) & \mu c\Gamma A(x_2) & \ldots & \mu c\Gamma A(x_n)
\end{array}
$$

If $a_{ij} = \mu c\Gamma A(x_j)$ for $j=1,2,\ldots,n$, then the cardinal set $c\Gamma A_\lambda$ is uniquely characterised by a matrix,

$$
[a_{ij}]_{1 \times n} = [a_{11}, a_{12}, \ldots, a_{1n}]
$$
Which is called the cardinal matrix of the cardinal set cΓ over E.

D. Step 4:

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

\[ \text{FSagg : } c\text{FS}(U) \times \text{FS}(U) \rightarrow \text{F}(U) \text{, } \text{FSagg}(c\Gamma_A, \Gamma_A) = \Gamma^*_A \]

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

\[ \mu_{\Gamma^*_A} : U \rightarrow [0, 1] \text{, } \mu_{\Gamma^*_A}(u) = \sum_{x \in E} \mu_{c\Gamma_A(x)}(x) \]

where \( |E| \) is the cardinality of E.

Now assume that \( U = \{ u_1, u_2, \ldots, u_m \} \), then the \( \Gamma^*_A \) can be presented by the following table.

<table>
<thead>
<tr>
<th>ΓA</th>
<th>( \mu_{\Gamma^*_A} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>u1</td>
<td>( \mu_{\Gamma^*_A}(u1) )</td>
</tr>
<tr>
<td>u2</td>
<td>( \mu_{\Gamma^*_A}(u2) )</td>
</tr>
<tr>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>um</td>
<td>( \mu_{\Gamma^*_A}(um) )</td>
</tr>
</tbody>
</table>

If \( a_{ij} = \mu_{\Gamma^*_A}(u_i) \) for \( i=1,2,\ldots,m \) then \( \Gamma^*_A \) is uniquely characterised by the matrix

\[
[a_{ij}]^{mx1} = \begin{bmatrix}
  a_{11} \\
  a_{21} \\
  . \phantom{,} . \\
  . \phantom{,} . \\
  . \phantom{,} . \\
  a_{m1}
\end{bmatrix}
\]

Which is called the aggregate matrix of \( \Gamma^*_A \) over U.

If \( M\Gamma_A, M\Gamma_A, M\Gamma^*_A \) are representation matrices of \( \Gamma_A \), \( c\Gamma_A \) and \( \Gamma^*_A \), respectively then

\[ |E| \times M\Gamma^*_A = M\Gamma_A \times M^T \Gamma_A \]

Then \( M\Gamma^*_A = \sum_{M\Gamma_A \times M^T \Gamma_A} |E| \]

Where \( M^T \Gamma_A \) is the transposition of \( M \Gamma_A \) and \( |E| \) is the cardinality of E.

E. Step 5

Find the best alternative from this aggregate fuzzy set \( \Gamma^*_A \) that has the largest membership grade by \( \max \mu_{\Gamma^*_A}(u) \).
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 \( \Gamma A_1, \Gamma A_2, \Gamma A_3 \) over \( U \) as follow:

<table>
<thead>
<tr>
<th>( \Gamma A_1 )</th>
<th>( x_1 )</th>
<th>( x_2 )</th>
<th>( x_3 )</th>
<th>( x_4 )</th>
<th>( x_5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( c_1 )</td>
<td>0.8</td>
<td>0.6</td>
<td>0.4</td>
<td>0.6</td>
<td>0.4</td>
</tr>
<tr>
<td>( c_2 )</td>
<td>0.7</td>
<td>0.6</td>
<td>0.4</td>
<td>0.6</td>
<td>0.7</td>
</tr>
<tr>
<td>( c_3 )</td>
<td>0.6</td>
<td>0.5</td>
<td>0.4</td>
<td>0.6</td>
<td>0.5</td>
</tr>
<tr>
<td>( c_4 )</td>
<td>0.9</td>
<td>0.6</td>
<td>0.3</td>
<td>0.9</td>
<td>0.5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>( \Gamma A_2 )</th>
<th>( x_1 )</th>
<th>( x_2 )</th>
<th>( x_3 )</th>
<th>( x_4 )</th>
<th>( x_5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( c_1 )</td>
<td>0.6</td>
<td>0.5</td>
<td>0.2</td>
<td>0.8</td>
<td>0.5</td>
</tr>
<tr>
<td>( c_2 )</td>
<td>0.6</td>
<td>0.5</td>
<td>0.5</td>
<td>0.4</td>
<td>0.6</td>
</tr>
<tr>
<td>( c_3 )</td>
<td>0.4</td>
<td>0.6</td>
<td>0.4</td>
<td>0.5</td>
<td>0.7</td>
</tr>
<tr>
<td>( c_4 )</td>
<td>0.8</td>
<td>0.4</td>
<td>0.2</td>
<td>0.7</td>
<td>0.5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>( \Gamma A_3 )</th>
<th>( x_1 )</th>
<th>( x_2 )</th>
<th>( x_3 )</th>
<th>( x_4 )</th>
<th>( x_5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( c_1 )</td>
<td>0.7</td>
<td>0.4</td>
<td>0.3</td>
<td>0.7</td>
<td>0.6</td>
</tr>
<tr>
<td>( c_2 )</td>
<td>0.5</td>
<td>0.7</td>
<td>0.3</td>
<td>0.5</td>
<td>0.5</td>
</tr>
<tr>
<td>( c_3 )</td>
<td>0.5</td>
<td>0.7</td>
<td>0.4</td>
<td>0.4</td>
<td>0.6</td>
</tr>
<tr>
<td>( c_4 )</td>
<td>0.7</td>
<td>0.5</td>
<td>0.4</td>
<td>0.8</td>
<td>0.5</td>
</tr>
</tbody>
</table>

So taking the average of the above three soft sets \( \Gamma A_1, \Gamma A_2, \Gamma A_3 \) we get the performance fs-set \( \Gamma A \) over \( U \).

Step 2.: Construct an fs-set \( \Gamma A \) over \( U \) as given in the following table
Then \([atf]_{mxn}\) is called an m x n fs-matrix of the fs- set \(\Gamma A\) over \(U\) as given below.

\[
\begin{bmatrix}
0.7 & 0.5 & 0.3 & 0.7 & 0.5 \\
0.6 & 0.6 & 0.4 & 0.5 & 0.6 \\
0.5 & 0.6 & 0.4 & 0.5 & 0.6 \\
0.8 & 0.5 & 0.3 & 0.8 & 0.5 \\
\end{bmatrix}
\]

Step 3: The cardinal set \(c\Gamma A\) of \(\Gamma A\) is computed as follows:

\[
\mu c\Gamma a(x1) = (0.7+0.6+0.5+0.8)/4=0.65
\]
\[
\mu c\Gamma a(x2) = (0.5+0.6+0.6+0.5+)/4=0.55
\]
\[
\mu c\Gamma a(x3) = (0.3+0.4+0.4+0.3)/4=0.35
\]
\[
\mu c\Gamma a(x4) = (0.7+0.5+0.5+0.8)/4=0.625
\]
\[
\mu c\Gamma a(x5) = (0.5+0.6+0.6+0.5)/4=0.55
\]

So cardinal set \(c\Gamma A = \{0.65/x_1, 0.55/x_2, 0.35/x_3, 0.625/x_4, 0.55/x_5\}\)

Step 4: The aggregate fuzzy set \(M\Gamma*A\) is computed as follows:

\[
\begin{bmatrix}
0.7 & 0.5 & 0.3 & 0.7 & 0.5 \\
0.6 & 0.6 & 0.4 & 0.5 & 0.6 \\
0.5 & 0.6 & 0.4 & 0.5 & 0.6 \\
0.8 & 0.5 & 0.3 & 0.8 & 0.5 \\
\end{bmatrix}
\]

\[
M\Gamma*A= \frac{1}{5}
\]

<table>
<thead>
<tr>
<th>0.7</th>
<th>0.5</th>
<th>0.3</th>
<th>0.7</th>
<th>0.5</th>
<th>0.65</th>
<th>0.310</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.6</td>
<td>0.6</td>
<td>0.4</td>
<td>0.5</td>
<td>0.6</td>
<td>0.55</td>
<td>0.301</td>
</tr>
<tr>
<td>0.5</td>
<td>0.6</td>
<td>0.4</td>
<td>0.5</td>
<td>0.6</td>
<td>0.35</td>
<td>0.288</td>
</tr>
<tr>
<td>0.8</td>
<td>0.5</td>
<td>0.3</td>
<td>0.8</td>
<td>0.5</td>
<td>0.625</td>
<td>0.335</td>
</tr>
<tr>
<td>0.55</td>
<td>0.35</td>
<td>0.625</td>
<td>0.288</td>
<td>0.335</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

That means,

\(\Gamma*A = \{0.310/c_1, 0.301/c_2, 0.288/c_3, 0.355/c_4\}\)

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

Which means that the city \(c_4\) has the largest membership grade, hence \(c_4\) is the best suitable city which has the parameters as \(x_1=0.8, x_2=0.3, x_3=0.8, x_4=0.5, x_5=0.5\). 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.

Acknowledgement

The author would like to thank the anonymous referees for their comments that helped me improve this article.

Competing Interests

Author has declared that no competing interests exist.

References


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Peer-review history:
The peer review history for this paper can be accessed here (Please copy paste the total link in your browser address bar)
http://www.sciencedomain.org/review-history/27795