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A new approach in handling soft decision making problems

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Abstract

The goal of this paper is to bring a new approach to the computation of the decision making problems by using inverse (fuzzy) soft sets instead of (fuzzy) soft sets which makes the algorithms easier and faster than the existed methods. For this purpose, we first define inverse soft sets and inverse fuzzy soft sets. Then we use them to solve decision making problems in a slightly modified way.

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1. Introduction

A number of real life problems in engineering, social and medical sciences, economics etc. involve imprecise data and their solution involves the use of mathematical principles based on uncertainty and imprecision. Some of these problems are essentially humanistic and thus subjective in nature (e.g. human understanding and vision systems), while others are objective, yet they are firmly embedded in an imprecise environment. In recent years a number of theories have been proposed for dealing with such systems in an effective way such as, theory of fuzzy sets [15], intuitionistic fuzzy sets [3], rough sets [13], i.e., which we can use as a mathematical tools for dealing with uncertainties. As it was mentioned in [12], these theories have their own difficulties. In 1999, Molodtsov [12] initiated a novel concept of soft set theory, which is a completely new approach for modeling vagueness and uncertainty.

Applications of Soft Set Theory in other disciplines and real life problems are now catching momentum. Molodtsov [12] successfully applied the soft set theory into several directions. Maji et al. [9, 10] gave first

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practical application of soft sets in decision making problems. They have also introduced the concept of fuzzy soft set, a more generalized concept, which is a combination of fuzzy set and soft set and also studied some of its properties. Soft set and fuzzy soft set theories have a rich potential for applications in several directions, few of which had been shown by some authors [1, 2, 5, 6, 7, 8, 12, 14].

The problem of decision making in an imprecise environment has found paramount importance in recent years. In [4], Çağman and Enginoğlu introduced *uni-int* operators and constructed *uni-int* decision making method which can be applied to a problem with two decision makers. This method select a set of optimum elements reducing the initial set according to the parameters of decision makers by using *uni-int* operators and allows decision makers to work on small number of alternatives instead of large numbers. Besides having some good properties of this method it has also some disadvantages. Since it is difficult to define *uni-int* operators for product of three or more soft sets, this method can not be applied to a problem with three or more decision makers in a simple and appropriate way.

The aim of this paper is to point out the importance of the decision making problems and give a new approach to find the optimal solution in an easier and faster way than the existed algorithms. So, we first give the definitions of inverse soft sets and inverse fuzzy soft sets. Then we handle the decision making problems proposed by Çağman et al.[4], Maji et al.[14] and reconsider them by using new algorithms based on inverse soft sets and inverse fuzzy soft sets, respectively. In conclusion, we obtain the same results without calculating any other (fuzzy) soft sets or using (fuzzy) soft set operations.

2. Preliminaries

Throughout this paper, X and E refers to an initial universe and the set of all parameters for X, respectively. Also, A, B and C denote the subsets of E, otherwise specified.

2.1. Inverse soft sets

Definition 2.1 ([4])**.** A soft set F_A on the universe X is a mapping from the parameter set E to the power set $P(X)$ of X, i.e., $F_A : E \longrightarrow P(X)$, where $F_A(e) \neq \emptyset$, if $e \in A \subseteq E$ and $F_A(e) = \emptyset$ if $e \notin A$. A soft set can also be defined by the set of ordered pairs

$$F_A = \{(e, F_A(e)) : e \in E, F_A(e) \in P(X)\}.$$

The value $F_A(e)$ is a set called $e-$element of the soft set for all $e \in E$.

Example 2.2 ([12])**.** A soft set (F, E) describes the attractiveness of the houses which Mr. A is going to buy.
X = The set of houses under consideration.
E = The set of parameters. Each parameter is a word or sentence.
$E = \{expensive, beautiful, wooden, cheap, in\ the\ green\ surrounding, modern, in\ good\ repair, in\ bad\ repair\}$.
In this case, to define a soft set means to point out expensive houses, beautiful houses, and so on.It is worth noting that the sets $F(e)$ may be empty for some $e \in E$.

Definition 2.3. A mapping $\Lambda : X \longrightarrow P(E)$ is called an inverse soft set (for short, ISS) on X.

Note that an ISS can be seen as a collection of subsets of the parameter set E, i.e., $\Lambda = \{\Lambda(x)\}_{x \in X} \subseteq P(E)$. Since the power set is a lattice under the set inclusion, an ISS can be thought as a special kind of fuzzy set which has the soft set properties.

For an ISS Λ on X, the subset $\Lambda(x)$ of E denotes the membership parameters of x to the ISS Λ and $E \setminus \Lambda(x)$ denotes the non-membership parameters of x to the ISS Λ. The family of all ISSs on X is denoted by $ISS(X)$.

Each soft set can be uniquely represented as an ISS in the following manner.

Remark 2.4. Let (F, A) be a soft set on X, where $A \subseteq E$ is the parameter set. By using the mapping $F : A \longrightarrow P(X)$, we define a parameterized family $\overline{F} = \{F^{\leftarrow}(x) : x \in X\}$ which is an ISS on X, where $F^{\leftarrow}(x) \triangleq \{e : x \in F(e)\}$. On the other hand, if we know the resulting ISS $\overline{F} = \{F^{\leftarrow}(x) : x \in X\}$, we can find the initial soft set by using the mapping $\overline{F} : X \longrightarrow P(E)$, that is, $(F, A) = \{\left(\overline{F}\right)^{\leftarrow}(e) : e \in A\}$, where $A = \cup_{x\in X} F^{\leftarrow}(x)$. Therefore, a soft set can be uniquely represented as an inverse soft set.

Example 2.5. Suppose λ be a fuzzy set, that is, $\lambda : X \longrightarrow [0, 1]$, and take $E = [0, 1]$ as the parameter set. By using the mapping $\lambda : X \longrightarrow [0, 1]$ we construct a unique ISS $\overline{\lambda} : X \longrightarrow P(E)$, by $\overline{\lambda}(x) = [0, \lambda(x))$. Thus, each fuzzy set generates an ISS.

Definition 2.6. Let Λ be an ISS on X. Then

(1) Λ is called an empty ISS, denoted by Φ, if $\Lambda(x) = \emptyset$, for all $x \in X$;
(2) Λ is called an A-universal ISS, denoted by $\widetilde{A}$, if $\Lambda(x) = A$, for all $x \in X$. If $A = E$, then Λ is called a universal ISS, denoted by $\widetilde{E}$;
(3) the complement of Λ, denoted by Λ^c, is an inverse soft set defined by $\Lambda^c(x) = E \setminus \Lambda(x)$.

Definition 2.7. Let Λ, Σ be two ISSs on X.Then

(1) Λ is a subset of Σ, denoted by $\Lambda \sqsubseteq \Sigma$, if $\Lambda(x) \subseteq \Sigma(x)$, for each $x \in X$. Λ and Σ are said to be equal, denoted by $\Lambda = \Sigma$, if $\Lambda(x) = \Sigma(x)$, for each $x \in X$;
(2) the union of Λ and Σ, denoted by $\Lambda \sqcup \Sigma$, is an inverse soft set defined by $(\Lambda \sqcup \Sigma)(x) = \Lambda(x) \cup \Sigma(x)$, for each $x \in X$;
(3) the intersection of Λ and Σ, denoted by $\Lambda \sqcap \Sigma$, is an inverse soft set defined by $(\Lambda \sqcap \Sigma)(x) = \Lambda(x) \cap \Sigma(x)$, for each $x \in X$.

2.2. Inverse fuzzy soft sets

Definition 2.8 ([11]). Let I^X denotes the set of all fuzzy sets on X and $A \subset E$. A pair (f, A) is called a fuzzy soft set over X, where f is a mapping from A into I^X. That is, for each $a \in A$, $f(a) = f_a : X \longrightarrow I$, is a fuzzy set on X (where $I = [0, 1]$).

Definition 2.9. A mapping $F : X \longrightarrow I^E$ is called an inverse fuzzy soft set (for short, IFSS) on X.

Note that, the elements of IFSSs are fuzzy sets on the parameter set E, i.e., for each $x \in X$, $F_x \triangleq F(x)$ is a fuzzy set on E. An IFSS can be seen as a multi-parameter fuzzy set. In this manner, F_x denotes the function of membership degree of x to the inverse fuzzy soft set F, for each $x \in X$ and $F_x(e)$ denotes the degree of membership of x to the inverse soft set F with respect to the parameter $e \in E$.

The family of all IFSSs on X is denoted by $IFSS(X)$.

Example 2.10. Consider the universal set $X = \{x_1, x_2, x_3, x_4\}$ which represents the set of houses and the parameter set $E = \{\text{green, large, small, expensive}\}$. Then the set of F defined as follows is an inverse fuzzy soft set.

$F(x_1) = \{e_1/0.4, e_2/0.1, e_3/0.6, e_4/0.4\}, F(x_2) = \{e_1/0.7, e_2/0.6, e_3/0.6, e_4/0.6\}$,
$F(x_3) = \{e_1/0.6, e_2/0.9, e_3/0.5, e_4/0.5\}, F(x_4) = \{e_1/0.5, e_2/0.1, e_3/0.8, e_4/0.8\}$.

Each fuzzy soft set can be uniquely represented as an IFSS in the following manner.

Remark 2.11. For a given fuzzy soft set (f, A) on X define $F_x : E \longrightarrow I$ by $F_x(e) = f(e)(x)$, for each $e \in A$ and $F_x(e) = 0$, for each $e \in E \setminus A$. Then $F : X \longrightarrow I^E$ is an IFSS on X. On the other hand, if we know the resulting IFSS F, we can find the initial soft set (f, A), where $f(e)(x) = F_x(e)$ and $A = \cup\{F_x(e) : F_x(e) > 0, x \in X\}$. Therefore, a fuzzy soft set can be uniquely represented as an inverse fuzzy soft set.

Example 2.12. A type-2 fuzzy set Λ [16] on X is a mapping from X to I^I. Now take $E = I$ as a parameter set. Then the type-2 fuzzy set $\Lambda : X \to I^E$ can be thought as a special kind of an IFSS.

Definition 2.13. Let F, G be the inverse fuzzy soft sets. Then,

(1) F is called a subset of G if $F_x \leqslant G_x$, for each $x \in X$ and it is denoted by $F \sqsubseteq G$. F and G are said to be equal if $F \sqsubseteq G$ and $G \sqsubseteq F$;
(2) union of the IFSSs F and G is an IFSS $H = F \sqcup G$, where $H_x = F_x \vee G_x$, for each $x \in X$;
(3) intersection of the IFSSs F and G is an IFSS $H = F \sqcap G$, where $H_x = F_x \wedge G_x$, for each $x \in X$;
(4) complement of an IFSS F is denoted by F^c, where $F^c : X \to I^E$ is a mapping given by $F^c_x = \overline{1} - F_x$, where $\overline{1}(e) = 1$, for each $e \in E$. Clearly $(F^c)^c = F$;
(5) F is called a null IFSS and denoted by Φ, if $F_x = \overline{0}$, for each $x \in X$, where $\overline{0}(e) = 0$, for each $e \in E$;
(6) F is called an absolute IFSS and denoted by $\widetilde{E}$, if $F_x = \overline{1}$, for each $x \in X$, where $\overline{1}(e) = 1$, for each $e \in E$. Clearly, $(\widetilde{E})^c = \Phi$ and $\Phi^c = \widetilde{E}$.

3. Decision making problem based on inverse soft sets

Algorithm
Step 1: Choose feasible subsets A, B of the set of parameters,
Step 2: Construct the inverse soft sets Λ, Σ for each set of parameters,
Step 3: Find all x which satisfy $[A \subseteq \Lambda(x)$ and $B \cap \Sigma(x) \neq \emptyset]$ or $[B \subseteq \Sigma(x)$ and $A \cap \Lambda(x) \neq \emptyset]$.

Example 3.1 ([4]). Assume that a company wants to fill a position. There are 48 candidates who fill in a form in order to apply formally for the position. There are two decision makers; one of them is from the department of human resources and the other one is from the board of directors. They want to interview the candidates.

Assume that the set of candidates $X = \{x_1, x_2, ..., x_{48}\}$ which may be characterized by a set of parameters $E = \{e_1, e_2, ..., e_7\}$. For $i = 1, 2, ..., 7$, the parameters e_i stand for "experience", "computer knowledge", "training", "young age", "higher education", "marriage status" and "good health", respectively.

Step 1: The decision makers consider set of parameters, $A = \{e_1, e_2, e_4, e_7\}$ and $B = \{e_1, e_2, e_5\}$, respectively, to evaluate the candidates.

Step 2: The decision makers seriously investigate CV of the candidates. After a serious discussion each candidate is evaluated from point of view of the goals and the constraint according to a chosen subset $A, B \subseteq E$. Then the decision makers construct the following two inverse soft sets on X according to their parameters, respectively.

$$\begin{aligned}\Lambda = \{&\Lambda(x_1) = \{e_2, e_7\}, \Lambda(x_2) = \{e_4\}, \Lambda(x_3) = \{e_2, e_4\}, \Lambda(x_4) = \{e_1\}, \Lambda(x_5) = \{e_7\}, \Lambda(x_6) = \emptyset,\\ &\Lambda(x_7) = \{e_1\}, \Lambda(x_8) = \emptyset, \Lambda(x_9) = \emptyset, \Lambda(x_{10}) = \emptyset, \Lambda(x_{11}) = \emptyset, \Lambda(x_{12}) = \{e_7\}, \Lambda(x_{13}) = \{e_1, e_2, e_4, e_7\},\\ &\Lambda(x_{14}) = \emptyset, \Lambda(x_{15}) = \{e_4\}, \Lambda(x_{16}) = \emptyset, \Lambda(x_{17}) = \{e_7\}, \Lambda(x_{18}) = \{e_2, e_4\}, \Lambda(x_{19}) = \{e_2\},\\ &\Lambda(x_{20}) = \{e_7\}, \Lambda(x_{21}) = \{e_1, e_2\}, \Lambda(x_{22}) = \{e_2\}, \Lambda(x_{23}) = \{e_4\}, \Lambda(x_{24}) = \{e_2, e_7\}, \Lambda(x_{25}) = \{e_4\},\\ &\Lambda(x_{26}) = \emptyset, \Lambda(x_{27}) = \emptyset, \Lambda(x_{28}) = \{e_1, e_2, e_4, e_7\}, \Lambda(x_{29}) = \{e_7\}, \Lambda(x_{30}) = \{e_4\}, \Lambda(x_{31}) = \{e_1\},\\ &\Lambda(x_{32}) = \{e_1, e_2\}, \Lambda(x_{33}) = \{e_4\}, \Lambda(x_{34}) = \{e_7\}, \Lambda(x_{35}) = \emptyset, \Lambda(x_{36}) = \{e_1, e_2, e_4, e_7\}, \Lambda(x_{37}) = \emptyset,\\ &\Lambda(x_{38}) = \{e_4\}, \Lambda(x_{39}) = \{e_1\}, \Lambda(x_{40}) = \emptyset, \Lambda(x_{41}) = \{e_1, e_7\}, \Lambda(x_{42}) = \{e_2, e_4\}, \Lambda(x_{43}) = \{e_1\},\\ &\Lambda(x_{44}) = \{e_1, e_2\}, \Lambda(x_{45}) = \{e_7\}, \Lambda(x_{46}) = \{e_2\}, \Lambda(x_{47}) = \{e_7\}, \Lambda(x_{48}) = \{e_1\}\},\end{aligned}$$

$$\begin{aligned}\Sigma = \{&\Sigma(x_1) = \{e_2\}, \Sigma(x_2) = \{e_5\}, \Sigma(x_3) = \{e_1\}, \Sigma(x_4) = \{e_1, e_2, e_5\}, \Sigma(x_5) = \{e_1\}, \Sigma(x_6) = \emptyset,\\ &\Sigma(x_7) = \{e_2\}, \Sigma(x_8) = \{e_1, e_5\}, \Sigma(x_9) = \{e_5\}, \Sigma(x_{10}) = \{e_2\}, \Sigma(x_{11}) = \{e_2\}, \Sigma(x_{12}) = \{e_5\},\\ &\Sigma(x_{13}) = \{e_2, e_5\}, \Sigma(x_{14}) = \{e_1, e_5\}, \Sigma(x_{15}) = \{e_2\}, \Sigma(x_{16}) = \{e_5\}, \Sigma(x_{17}) = \{e_5\}, \Sigma(x_{18}) = \emptyset,\\ &\Sigma(x_{19}) = \emptyset, \Sigma(x_{20}) = \emptyset, \Sigma(x_{21}) = \{e_1, e_2, e_5\}, \Sigma(x_{22}) = \{e_1\}, \Sigma(x_{23}) = \{e_5\}, \Sigma(x_{24}) = \emptyset,\end{aligned}$$

$$\Sigma(x_{25})=\emptyset,\Sigma(x_{26})=\{e_1\},\Sigma(x_{27})=\{e_1\},\Sigma(x_{28})=\{e_5\},\Sigma(x_{29})=\{e_2\},\Sigma(x_{30})=\{e_2\},$$
$$\Sigma(x_{31})=\emptyset,\Sigma(x_{32})=\{e_2\},\Sigma(x_{33})=\emptyset,\Sigma(x_{34})=\{e_1\},\Sigma(x_{35})=\{e_1\},\Sigma(x_{36})=\{e_2,e_5\},$$
$$\Sigma(x_{37})=\{e_1\},\Sigma(x_{38})=\emptyset,\Sigma(x_{39})=\emptyset,\Sigma(x_{40})=\{e_1\},\Sigma(x_{41})=\emptyset,\Sigma(x_{42})=\{e_1,e_2,e_5\},$$
$$\Sigma(x_{43})=\{e_2\},\Sigma(x_{44})=\{e_5\},\Sigma(x_{45})=\{e_2\},\Sigma(x_{46})=\{e_1\},\Sigma(x_{47})=\emptyset,\Sigma(x_{48})=\emptyset\}.$$

Step 3: Simply we have the decision set $\{x_4, x_{13}, x_{21}, x_{28}, x_{36}, x_{42}\}$.

The above problem considered by Çağman et al. [4] by using different tools named uni-int decision operators. To apply this method they advised to compute not only soft sets but also product of them and choose the right operation which takes lots of time especially under consideration of more than two parameter sets. So, we found it reasonable to propose a new approach to a soft set called inverse soft set and apply this to a decision making problems. As seen above example this theory is more convenient for applications. It is simple to use, no need to compute any other operators and so, faster than the other algorithms. Moreover, this method can be constructed easily if finite chosen parameter sets are under consideration such as $A_1, A_2, ..., A_n \subseteq E$. Let us give the generalization of this method for given n parameter sets as in the following.

Algorithm

Step 1: Choose feasible subsets $A_1, A_2, ..., A_n$ of the set of parameters.

Step 2: Construct the inverse soft sets $\Lambda_i, i = 1, ..., n$, for each set of parameter sets.

Step 3: Find all x which satisfy $A_i \subseteq \Lambda_i(x)$, $\exists i \in \{1, 2, ..., n\}$, and $A_j \cap \Lambda_j(x) \neq \emptyset$, $\forall j \neq i$.

Let us consider the same example for a given additional parameter subset $C = \{e_3, e_6, e_7\}$. Consider the third inverse soft set Ω which is given by the parameterized family

$$\Omega=\{\Omega(x_1)=\{e_3,e_6\},\Omega(x_2)=\{e_7\},\Omega(x_3)=\{e_3,e_6,e_7\},\Omega(x_4)=\{e_3,e_6\},\Omega(x_5)=\emptyset,$$
$$\Omega(x_6)=\{e_3,e_6,e_7\},\Omega(x_7)=\emptyset,\Omega(x_8)=\{e_6\},\Omega(x_9)=\emptyset,\Omega(x_{10})=\{e_7\},\Omega(x_{11})=\{e_7\},$$
$$\Omega(x_{12})=\{e_3\},\Omega(x_{13})=\{e_6,e_7\},\Omega(x_{14})=\{e_6\},\Omega(x_{15})=\{e_7\},\Omega(x_{16})=\emptyset,\Omega(x_{17}))=\emptyset,$$
$$\Omega(x_{18})=\{e_7\},\Omega(x_{19})=\emptyset,\Omega(x_{20})=\{e_6\},\Omega(x_{21})=\emptyset,\Omega(x_{22})=\{e_7\},\Omega(x_{23})=\{e_7\},\Omega(x_{24})=\emptyset,$$
$$\Omega(x_{25})=\{e_7\},\Omega(x_{26})=\{e_6\},\Omega(x_{27})=\{e_6\},\Omega(x_{28})=\{e_6,e_7\},\Omega(x_{29})=\{e_3\},\Omega(x_{30})=\emptyset,$$
$$\Omega(x_{31})=\emptyset,\Omega(x_{32})=\{e_7\},\Omega(x_{33})=\emptyset,\Omega(x_{34})=\{e_3\},\Omega(x_{35})=\emptyset,\Omega(x_{36})=\{e_3,e_7\},$$
$$\Omega(x_{37})=\{e_6\},\Omega(x_{38})=\emptyset,\Omega(x_{39})=\emptyset,\Omega(x_{40})=\{e_7\},\Omega(x_{41})=\{e_6,e_7\},\Omega(x_{42})=\{e_3\},$$
$$\Omega(x_{43})=\emptyset,\Omega(x_{44})=\{e_6\},\Omega(x_{45})=\{e_7\},\Omega(x_{46})=\emptyset,,\Omega(x_{47})=\{e_7\},\Omega(x_{48})=\{e_3\}\}.$$

Step 3: We have the decision set $\{x_3, x_4, x_{13}, x_{28}, x_{36}, x_{42}\}$.

Besides the above algorithms, let us support our idea in theoretical manner by the following theorem which emphasizes the equivalence of method of Çağman et al.[4] and our approach.

Theorem 3.2. *Let F_A, G_B be soft sets over X and Λ, Σ be the corresponding inverse soft sets, respectively. Then, $x \in uni - int(F_A \wedge G_B)$ if and only if [$A \subseteq \Lambda(x)$ and $B \cap \Sigma(x) \neq \emptyset$] or [$B \subseteq \Sigma(x)$ and $A \cap \Lambda(x) \neq \emptyset$].*

Proof. Let $x \in uni - int(F_A \wedge G_B)$

$\Leftrightarrow x \in uni_e int_k(F_A \wedge G_B)$ or $x \in uni_k int_e(F_A \wedge G_B)$

$\Leftrightarrow [x \in \cup_{e\in A} (\cap_{k\in B}(F_A \wedge G_B)(e, k))]$ or $[x \in \cup_{k\in B} (\cap_{e\in A}(F_A \wedge G_B)(e, k))$

$\Leftrightarrow [\exists e \in A$ and $\forall k \in B, x \in F_A(e) \cap G_B(k)]$ or $[\exists k \in B$ and $\forall e \in A, x \in F_A(e) \cap G_B(k)]$

$\Leftrightarrow [\exists e \in A$ and $\forall k \in B, e \in \Lambda(x), k \in \Sigma(x)]$ or $[\exists k \in B$ and $\forall e \in A, e \in \Lambda(x), k \in \Sigma(x)]$

$\Leftrightarrow [\Lambda(x) \cap A \neq \emptyset$ and $, B \subseteq \Sigma(x)]$ or $[\Sigma(x) \cap B \neq \emptyset$ and $, A \subseteq \Lambda(x)]$. □

4. Decision making problem based on inverse fuzzy soft sets

Let $U = \{x_1, x_2, x_3, x_4, x_5, x_6\}$ be the set of objects having different colors, sizes and surface texture features. The parameter set, $E = \{$blackish, dark brown, yellowish, reddish, large, small, very small, average, very large, course, moderately course, fine, extra fine$\}$. Let A, B and C be the subsets of E. Also let A represents the color space and B represents the size of the object. $A = \{$blackish, dark brown, yellowish, reddish $\}$, $B = \{$ large, very large, small, very small, average$\}$. The subset C represents the surface texture granularity, i.e., $C = \{$ course, moderately course, fine, extra fine $\}$.

Assuming that the fuzzy-soft-set (F, A) describe the objects having color space, the fuzzy-soft-set (G, B) describes the objects having size and the fuzzy-soft-set (H, C) describes the texture feature of the object surface. The problem here is to choose an object from the set of given objects with respect to a set of choice parameters P. We now first recall an algorithm for identification of an object, based on multiobservers input data characterized by color, size and surface texture features given by Maji et al.[14] and then present a new algorithm to find the optimal solution of the same problem by using inverse fuzzy soft sets.

U	"blackish" $= a_1$	"dark brown" $= a_2$	"yellowish" $= a_3$	"reddish" $= a_4$
x_1	0.3	0.4	0.6	0.9
x_2	0.3	0.9	0.3	0.5
x_3	0.4	0.5	0.8	0.7
x_4	0.8	0.2	0.4	0.8
x_5	0.7	0.3	0.6	0.5
x_6	0.9	0.2	0.4	0.3

Table 1: Fuzzy soft set (F, A)

U	"large" $= b_1$	"very large" $= b_2$	"small" $= b_3$	"very small" $= b_4$	"average" $= b_5$
x_1	0.4	0.2	0.8	0.6	0.5
x_2	0.8	0.6	0.3	0.1	0.7
x_3	0.6	0.4	0.4	0.1	0.7
x_4	0.9	0.8	0.2	0.1	0.4
x_5	0.2	0.1	0.9	0.8	0.7
x_6	0.3	0.2	0.8	0.6	0.5

Table 2: Fuzzy soft set (G, B)

U	"course" $= c_1$	"moderately course" $= c_2$	"fine" $= c_3$	"extra fine" $= c_4$
x_1	0.3	0.4	0.1	0.9
x_2	0.6	0.5	0.4	0.5
x_3	0.5	0.6	0.3	0.6
x_4	0.7	0.6	0.6	0.3
x_5	0.6	0.6	0.5	0.4
x_6	0.8	0.7	0.7	0.9

Table 3: Fuzzy soft set (H, C)

4.1. Roy and Maji's method

Algorithm 1 ([14])

1. Input the fuzzy soft sets (F, A), (G, B) and (H, C).
2. Input the parameter set P as observed by the observer.

3. Compute the corresponding resultant fuzzy soft set (S, P) from the fuzzy soft sets (F, A), (G, B), (H, C) and place it in tabular form.
4. Construct the Comparison-table of the fuzzy soft set (S, P) and compute r_i and t_i for x_i , $\forall i$.
5. Compute the score S_i of x_i , $\forall i$.
6. The decision is S_k if, $S_k = \max_i S_i$.
7. If k has more than one value then any one of x_k may be chosen.

The comparison table is a square table in which rows and columns both are labeled by the object names $x_1, x_2, ..., x_n$ of the universe, and the entries c_{ij} indicate the number of parameters for which the membership value of x_i exceeds or equals the membership value of x_j . Clearly, $0 \leq c_{ij} \leq m$ and $c_{ii} = m$ $(\forall i, j)$, where m is the number of parameters. The row-sum r_i and the column sum t_i of an object x_i is computed by $r_i = \sum_{j=1}^{n} c_{ij}$ and $t_i = \sum_{i=1}^{n} c_{ij}$, respectively.

The representation of the resultant fuzzy soft set (S, P), comparison table (S, P) and score table of (S, P) [14] is given in the Table 4, Table 5 and Table 6, respectively.

U	e_1	e_2	e_3	e_4	e_5	e_6	e_7
x_1	0.3	0.1	0.4	0.4	0.1	0.1	0.5
x_2	0.3	0.3	0.5	0.1	0.3	0.1	0.5
x_3	0.4	0.3	0.5	0.1	0.3	0.1	0.6
x_4	0.7	0.4	0.2	0.1	0.2	0.1	0.3
x_5	0.2	0.5	0.2	0.3	0.5	0.5	0.4
x_6	0.3	0.5	0.2	0.2	0.4	0.3	0.3

Table 4: The representation table of (S, P)

	x_1	x_2	x_3	x_4	x_5	x_6
x_1	7	4	2	4	4	4
x_2	6	7	5	5	3	3
x_3	6	7	7	5	3	3
x_4	4	4	4	7	2	3
x_5	3	4	4	6	7	6
x_6	4	5	4	6	3	7

Table 5: The Comparison table of (S, P)

	r_i	t_i	Score (S_i)
x_1	25	30	-5
x_2	29	31	-2
x_3	31	26	5
x_4	24	33	-7
x_5	30	22	8
x_6	29	26	3

Table 6: The score table of (S, P)

Finally, the score S_i of an object is defined by $S_i = r_i - t_i$. From the Table 6, it is clear that x_5 has the maximum score $S_5 = 8$; hence by the Algorithm 1, the optimal decision is x_5.

4.2. A method based on inverse fuzzy soft sets

Now we use the inverse fuzzy soft sets to solve this problem. We can construct an IFSS $\Lambda : U \longrightarrow I^E$ (Figure 1) by using (F, A), (G, B) and (H, C), where $E = A \cup B \cup C$.

In Fig.1; the red dots denote the set of $\Lambda(x_1)$, the dark blue dots denote the set of $\Lambda(x_2)$, the blue dots denote the set of $\Lambda(x_3)$, the green dots denote the set of $\Lambda(x_4)$, the yellow dots denote the set of $\Lambda(x_5)$ and the purple dots denote set of $\Lambda(x_6)$.

Algorithm 2

1. Input the inverse fuzzy soft set Λ.
2. Input the parameter sets $A_i \subset E$ as observed by the observer.
3. Compute the values $\min\{\Lambda(x_i)(e) : e \in A_j\}$ $(\forall i, j)$ and put in the $(x_i - A_i)$-table.

4. Construct the Comparison-table set and compute r_i and t_i for x_i , $\forall i$.
5. Compute the score S_i of x_i , $\forall i$.
6. The decision is S_k if, $S_k = \max_i S_i$.
7. If k has more than one value then any one of x_k may be chosen.

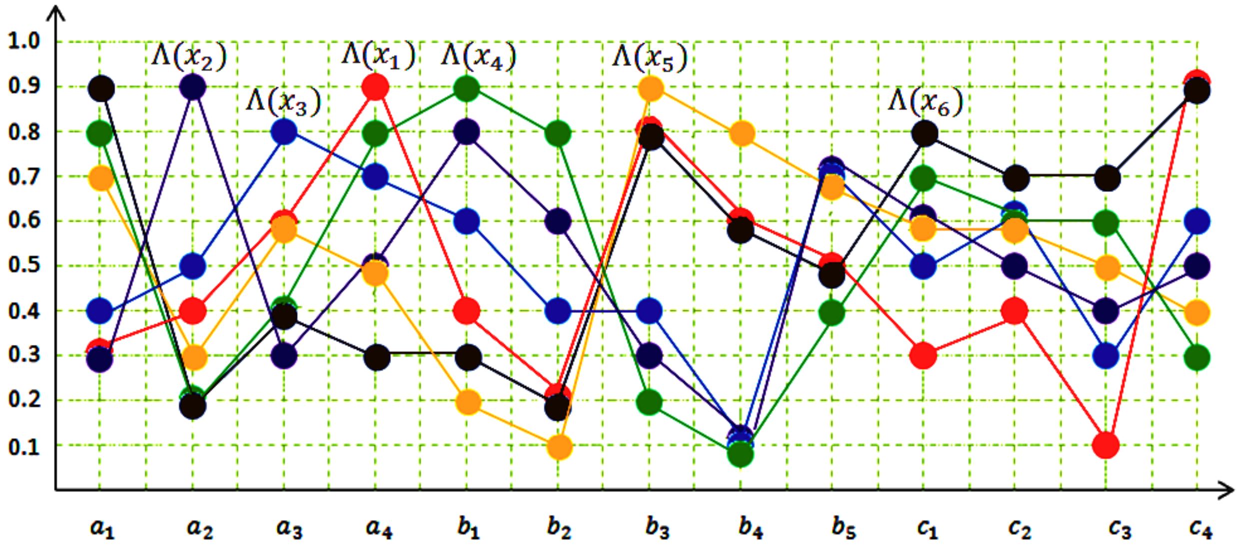

Figure 1: The elements of inverse fuzzy soft set

The Algorithm 2 is slightly different from the algorithm 1. In step 2, we use parameter subsets $A_1, A_2, ..., A_7$ of E instead of the parameter set $P = \{e_1 = a_1 \wedge a_2 \wedge c_1, e_2 = a_1 \wedge b_5 \wedge c_3, e_3 = a_2 \wedge b_1 \wedge c_2, e_4 = a_2 \wedge b_4 \wedge c_4, e_5 = a_3 \wedge b_3 \wedge c_3, e_6 = a_4 \wedge b_4 \wedge c_3, e_7 = a_4 \wedge b_5 \wedge c_4\}$, where $A_1 = \{a_1, a_2, c_1\}$, $A_2 = \{a_1, b_5, c_3\}, A_3 = \{a_2, b_1, c_2\}, A_4 = \{a_2, b_4, c_4\}, A_5 = \{a_3, b_3, c_3\}, A_6 = \{a_4, b_4, c_3\}, A_7 = \{a_4, b_5, c_4\}$. In step 3, there is no need to calculate an other fuzzy soft set, we only need to calculate the values $\min\{\Lambda(x_i)(e) : e \in A_j\}$ $(\forall i, j)$. On the other hand in Step 4 and 5 we find the same comparison table and score table. Hence, we have the same solution.

The advantages of using inverse fuzzy soft sets are: There is no need to input several fuzzy soft sets. We have only one inverse fuzzy soft set. Also, there is no need to use 'AND' operation. This operation makes computational works slower because in each time we apply 'AND' operation to fuzzy soft sets, the resulting fuzzy soft sets have larger and larger parameter set and that cause calculations of unnecessary datas. However, in this method, we only need to calculate what is asked.

5. Conclusion

In the present paper we aim to give an alternative way for computation of (fuzzy) soft decision making problems in more conveniently than the existed methods. Our strategy is based on the usage of inverse (fuzzy) soft sets instead of (fuzzy) soft sets as tools. By this way, we obtain the optimum results in an easier and faster way. According to our approach, there is no need to constitute any other set or no need to calculate any other operation except input data compared to soft decision making algorithms. This theory can be imposed similarly to the any other decision making problems.

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References

[1] A. Aygünoğlu, H. Aygün, *Introduction to fuzzy soft groups*, Comput. Math. Appl., **58** (2009), 1279–1286. 1

[2] A. Aygünoğlu, V. Çetkin, H. Aygün, *An introduction to fuzzy soft topological spaces*, Hacet. J. Math. Statist., **43** (2014), 197–208. 1

[3] K. Atanassov, *Intuitionistic fuzzy sets*, Fuzzy Sets and Systems, **20** (1986), 87–96. 1

[4] N. Çağman, S. Enginoğlu, *Soft set theory and uni-int decision making*, European J. Oper. Res., **207** (2010), 848–855. 1, 2.1, 3.1, 3

[5] D. Chen, E. C. C. Tsang, D. S. Yeung, X. Wang, *The parameterization reduction of soft set and its applications*, Comput. Math. Appl., **49** (2005), 757–763. 1

[6] F. Feng, Y. B. Jun c, X. Liu, L. Li, *An adjustable approach to fuzzy soft set based decision making*, J.Comput. Appl. Math., **234** (2010), 10–20. 1

[7] Y. Jiang, Y. Tang, Q. Chen, *An adjustable approach to intuitionistic fuzzy soft sets based decision making*, Appl. Math. Model., **35** (2011), 824–836. 1

[8] Y. B. Jun, K. J. Lee, C. H. Park, *Fuzzy soft set theory applied to BCK/BCI-algebras*, Comput. Math. Appl., **59** (2010), 3180–3192. 1

[9] P. K. Maji, A. R. Roy, *An application of soft set in decision making problem*, Comput. Math. Appli., **44** (2002), 1077–1083. 1

[10] P. K. Maji, R. Biswas, A. R. Roy, *Soft set theory*, Comput. Math. Appl., **45** (2003), 555–562. 1

[11] P. K. Maji, R. Biswas, A. R. Roy, *Fuzzy soft sets*, J. Fuzzy Math. **9** (2001), 589–602. 2.8

[12] D. Molodtsov, *Soft set theory-First results*, Comput. Math. Appl., **37** (1999), 19–31. 1, 2.2

[13] Z. Pawlak, *Rough sets*, Internat. J. Comput. Inform. Sci., **11** (1982), 341–356. 1

[14] A. R. Roy, P. K. Maji, *A fuzzy soft set theoretic approach to decision making problems*, J. Comput. Appl. Math., **203** (2007), 412–418. 1, 4, 4.1

[15] L. A. Zadeh, *Fuzzy sets*, Information and Control ,**8** (1965), 338–353. 1

[16] L. A. Zadeh, *The concept of a linguistic variable and its application to approxiamate reasoning - 1*, Information Sci. **8** (1975), 199–249. 2.12