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Research Article

Implementation of intuitionistic fuzzy soft set theoretic scheme in decision making

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ARTICLE INFO	ABSTRACT
Article History	Fuzzy soft set theory is becoming more and more important for coming up
Received: 18 December 2022 Revised: 02 April 2023 Accepted: 11 June 2023	with coherent and logical answers to numerous real-world issues that are riddled with uncertainty, imprecision, and vagueness. The intuitionistic fuzzy soft set was investigated theoretically later on. Wherever uncertainty resulting from ambiguity manifests in more sophisticated ways, the combination of
Keywords: Fuzzy soft set (FSS), Intuitionistic Fuzzy soft set (IFSS), Resultant IFSS, Comparison table.	intuitionistic fuzzy set and intuitionistic fuzzy soft set is more efficient from an implementational standpoint. In this paper, the motivation of our work is to establish a new methodology to select an object from an inexact multi- observer data with the idea of intuitionistic fuzzy soft set theory. Our methodology includes an algorithm based on "and", "or" operation, max, min comparison data and comparison table.

Introduction

Most of our modern life problems, such as socioeconomic, medical science and engineering, involve inexact data and some of these problems are basically humanistic. In current days so many theories have been developed to dealing with inexact situation in a feasible way. Fuzzy set theory (Roy and Maji 2007; Zadeh 1965; Zimmerman 1996; Prade and Dubois, 1980), Intuitionistic fuzzy set theory (Atanassov 1986, 1994; Islam et al., 2018; Mahbub et al., 2019), vague sets (Gau and Buehrer 1993), etc. are some of them, and can be employed as an adequate tool for dealing with any inexact circumstances and uncertainty situated in a discipline. However, all of these theories are consisting of some constraints, which is the lack of the parameterization tool accompanied with the mentioned theories. To avoid the limitations the idea of soft set theory is inaugurated by Molodtsov (1999), Pawlak (1982, 1994), etc. which has been employed in varied vexation. The problem of object determination has placed prime implication in this day. Majji et al., 2001; 2003 and Roy (2007) analyzes the concept of comparison table on SS theory and established a method for decision making problems. In this article we describe an application of IFSS theory in decision making problem and improve Majji and Roy (2001, 2003, 2007) given method to investigate a suitable object from a multi-observer data for a decision making problem. Section two consists of a summary note on the preliminaries concerned to FS theory and IFS theory. Later then section three explains a brief summary on soft set theory, fuzzy soft set theory and intuitionistic fuzzy soft set theory. The mathematical algorithm, used in our paper is illustrated in section four. A concise discussion of a decision making problem and its solution is illustrated in section five. Finally, the conclusion is narrated in section six.

Preliminary

In latter section we will briefly reflex the primary concept of FS and IFS which would be obligate for posterior platform.

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Fuzzy Set

Consider U be the universe of discourse. A fuzzy set V in U is characterized by a mapping μ_V from U to [0,1] (Zadeh 1965), that is, $\mu_V : U \rightarrow [0,1]$. Where, μ_V describes the grade of membership. Thus V can be defined by the set of order pair $V = \{(v, \mu_v(v)) | v \in U\}.$

Union of Two FS

The union of two fuzzy subsets A_1 and A_2 over

the same universe of discourse U is symbolized by $A_1 \bigcup A_2$ and is defined by (Zadeh 1965: Zimmerman 1996)

$$(A_1 \bigcup A_2)(a) = \{(a, \max(\mu_{A_1}(a), \mu_{A_2}(a))), \forall a \in U\}.$$

Intersection of Two FS

The intersection of two fuzzy subsets A_1 and A_2 over the same universe of discourse U is symbolized by $A_1 \bigcap A_2$ and is defined by (Zadeh 1965) $(A_1 \cap A_2)(a) = \{(a, \min(\mu_{A_1}(a), \mu_{A_2}(a))), \forall a \in U\}.$

Intuitionistic Fuzzy Set

Consider U be the universe of discourse. A IFS V in U is characterize by two mappings μ_V and γ_V from U to [0,1] (Atanassov et al., 1986), that is, $\mu_V: U \rightarrow [0,1]$ and $\gamma_V: U \rightarrow [0,1]$ such that value of μ_V and γ_V describe the grad of membership and non-grad of membership gradually. Thus V can be defined as the order triplet

$$V = \{(a, \mu_V(a), \gamma_V(a)) \mid a \in U\}$$

Here

$$(\mu_V(a) + \gamma_V(a)) \le 1$$

Union of Two IFS

Union of two IFS's A_1 and A_2 over the same universe of discourse U is symbolized by $A_1 \bigcup A_2$ and is defined for all $\forall a \in U$ as (Atanassov 1986)

 $(A_1 \bigcup A_2)(a) = \{(a, \max(\mu_{A_1}(a), \mu_{A_2}(a)), \min(\gamma_{A_1}(a), \gamma_{A_2}(a))\} \text{``and'' Operation of Two Soft Sets}\}$

Here

$$\mu_{A_1}(a) + \gamma_{A_1}(a) \le 1 \text{ and } \mu_{A_2}(a) + \gamma_{A_2}(a) \le \forall a \in U$$

Intersection of Two IFS

The intersection of two intuitionistic fuzzy subsets symbolized by $A_1 \cap A_2$ and is defined $\forall a \in U$ as

(Atanassov 1986)

$$(A_1 \cap A_2)(a) = \{(a, \min(\mu_{A_1}(a), \mu_{A_2}(a)), \max(\gamma_{A_1}(a), \gamma_{A_2}(a)))\}.$$

Here

$$\mu_{A_1}(a) + \gamma_{A_1}(a) \le 1 \text{ and } \mu_{A_2}(a) + \gamma_{A_2}(a) \le 1, \forall a \in U.$$

Fuzzy Soft Sets in Decision Making

This section consists of some basic definition of fuzzy soft set theory, great portion of them explained by Maji (2001). Let, the set of m objects $U = \{u_1, u_2, u_3, \dots, u_m\}$ is characterized by a set of parameters $\{E_1, E_2, E_3, \cdots, E_i\}$ The parameter extension Q may be formed as

$$Q \supseteq \{E_1, E_2, E_3, \cdots, E_i\},\$$

where each parameter set E_i stand for ith class of parameters and the components of E_i recite an especial characteristic set.

Soft Set

Presume U and Q is the universe of discourse and set of parameters gradually. For the power set P(U) of U and a subset B of Q define a mapping g from B to P(U) as $g: B \to P(U)$. The couple (g, P(U)) is known as a soft set on U (Molodtsov 1999; Roy and Maji 2007).

Soft Subset

Consider two soft sets (F_1, C_1) and (F_2, C_2) over the same universe of discourse U. Then (F_1, C_1) is said to be a subset of (F_2, C_2) if (Molodtsov 1999)

(i) $C_1 \subset C_2$ and

(ii) $\forall b \in B$, $f_1(b)$ and $f_2(b)$ are uniform approximations.

For two soft sets (F_1, C_1) and (F_2, C_2) over the same universe of discourse U, " (F_1, C_1) and (F_2, C_2) " is symbolized by $(F_1, C_1) \land (F_2, C_2)$ and is defined as (Molodtsov 1999)

$$(F_1, C_1) \wedge (F_2, C_2) = (F_3, C_1 \times C_2)$$

where

$$F_3(a,b) = F_1(a) \bigcap F_2(b), \forall (a,b) \in C_1 \times C_2.$$

"or" Operation of Two Soft Sets

For two soft sets (F_1, C_1) and (F_2, C_2) over the same universe of discourse U, " (F_1, C_1) or (F_2, C_2) " is symbolized as $(F_1, C_1) \lor (F_2, C_2)$ and is defined by (Molodtsov 1999)

where,

$$F_4(a,b) = F_1(a) \bigcup F_2(b), \forall (a,b) \in C_1 \times C_2.$$

 $(F_1, C_1) \lor (F_2, C_2) = (F_4, C_1 \times C_2),$

Fuzzy Soft Set

Presume P(U) to be the class of all fuzzy subsets of U and $E_i \subseteq Q$. Then the pair (f_i, E_i) is known as a FSS over U, where f_i describe a mapping from E_i to P(U) that is,

$$f_i: E_i \to P(U).$$

Fuzzy Soft Subset

Presume two FSS (F_1, C_1) and (F_2, C_2) over the same universe of discourse U. Then (F_1, C_1) is said to be a subset of (F_2, C_2) if (Roy and Maji 2007)

(i)
$$C_1 \subset C_2$$
, and

(ii) $\forall a \in C, F_1(a)$ is a fuzzy subset of $F_2(a)$.

"and" Operation of Two FSS

For two soft sets (F_1, C_1) and (F_2, C_2) over the same universe of discourse U, " (F_1, C_1) and (F_2, C_2) " is symbolized by $(F_1, C_1) \land (F_2, C_2)$ and is defined as (Molodtsov 1999)

$$(F_1, C_1) \wedge (F_2, C_2) = (F_3, C_1 \times C_2),$$

where

$$F_3(a,b) = F_1(a) \bigcap F_2(b), \forall (a,b) \in C_1 \times C_2.$$

"or" Operation of Two Fuzzy Soft Sets

Presume two FSS (F_1, C_1) and (F_2, C_2) over the same universe of discourse U. Then " (F_1, C_1) or (F_2, C_2) " is denoted by $(F_1, C_1) \lor (F_2, C_2)$ and is defined by (Roy and Maji 2007)

$$(F_1, C_1) \lor (F_2, C_2) = (F_4, C_1 \times C_2),$$

where,

$$F_4(a,b) = F_1(a) \bigcup F_2(b), \forall (a,b) \in C_1 \times C_2$$

Intuitionistic Fuzzy Soft Set

Suppose Q(U) explain the class of all IFS's of U and $E_i \subseteq Q$. IFSS over U is denoted by (g_i, E_i) where g_i defined as

$$g_i: E_i \to Q(U).$$

Intuitionistic Fuzzy Soft Subset

Consider two IFSS's (G_1, C_1) and (G_2, C_2) over the same universe of discourse U. Then (G_1, C_1) is said to be a subset of (G_2, C_2) if

- (i) $C_1 \subset C_2$, and
- (ii) $\forall a \in C_1, G_1(a)$ is a intuitionistic fuzzy subset of $G_2(a)$.

"and" operation of Two IFSS

Consider two IFSS's (G_1, C_1) and (G_2, C_2) over the same universe of discourse U. Then " (G_1, C_1) and (G_2, C_2) " is denoted by $(G_1, C_1) \wedge (G_2, C_2)$ and is defined by

 $(G_1, C_1) \wedge (G_2, C_2) = (G_3, C_1 \times C_2),$

where

$$G_3(a,b) = G_1(a) \bigcap G_2(b), \forall a \in C_1 \text{ and } b \in C_2$$

and " \cap " represent the intersection of two IFS.

"or" operation of Two IFSS

Consider two IFSS's (G_1, C_1) and (G_2, C_2) over the same universe of discourse U. Then " (G_1, C_1) or (G_2, C_2) " is denoted by $(G_1, C_1) \lor (G_2, C_2)$ and is defined by

$$(G_1, C_1) \lor (G_2, C_2) = (G_4, C_1 \times C_2),$$

where

$$G_4(a,b) = G_1(a) \bigcup G_2(b), \forall a \in C_1 \text{ and } b \in C_2$$

"U" represent the union of two intuitionistic fuzzy sets.

Comparison Table and Algorithm

In a comparison table count of rows and columns are identical and they are specified by the objects \mathcal{G}_i of the universe U. In our paper the entries C_{ij} of the comparison table is illustrated by the count of parameters for those the grade of membership \mathcal{G}_i differ or same to the grade of membership \mathcal{G}_i . If k describe count of parameters in a IFSS, then disputably $0 \le C_{ij} \le k$. If r_i and c_j represent the row sum and the column sum respectively of an object \mathcal{G}_i then it can be defined as

$$r_i = \sum_{j=1}^n C_{ij}$$
 and $c_j = \sum_{i=1}^n C_{ij}$,

where n represent the number of objects. In this paper our aim is to select an adequate object from a class of objects regarding to a class of choice parameters Q. We thus developed an algorithm to determinate an object from some multiobservers data specified by color, shape and price.

Algorithm

- 1. Input the parameter set Q.
- 2. Input the IFSS's (F_1, C) , (F_2, S) , and (F_3, P) .
- 3. Perform " (F_1, C) and (F_2, S) ".
- 4. Illustrate a comparison data for row max and row min in case of membership and non- membership value.
- 5. Select a new resultant IFSS (R_1, Q) , with respect to the comparison data.
- 6. Finally calculate the corresponding resultant IFSS (R_2, Q) , for the IFSS's (F_1, C) ,

 (F_2, S) , and (F_3, P) , and place it in tabular form.

- 7. Build up a comparison-table for the IFSS (R_2, Q) , and calculate r_i and c_i for all i.
- 8. Calculate $V_i = r_i c_i$, for all i, define as score.
- 9. If $V_k = \max\{V_i\}$, then the decision is V_k .

Application

Presume $O = \{ \mathcal{G}_1, \mathcal{G}_2, \mathcal{G}_3, \mathcal{G}_4, \mathcal{G}_5, \mathcal{G}_6 \}$, to be the class of components having varied colors, shape and price. Q={darkish, stone, grey, rosy, big, small, very small, medium, very big, very cheap, cheap, high, average}, represent the set of parameters consisting of three subsets C, S and P. Here C stands for color space, S for size space and P for price space gradually. Take IFSS (F_1, C) , relate the components having color space, IFSS (F_2, S) , relate the 'components having size' and IFSS (F_3, P) , relate the 'the components having price'. Our motivation is to ascertain the desired component from the multi observer's fuzzy data, mark by varied observers, in terms of IFSS $(F_1, C), (F_2, S), and (F_3, P),$ as described before. All of the three IFSS are represented in tabular form in Tables. l(a) - l(c).

	Darkish	Stone	Grey	Rosy
ϑ_1	(0.3, 0.4)	(0.4, 0.5)	(0.6, 0.2)	(0.9, 0.1)
ϑ_2	(0.3, 0.5)	(0.9, 0.1)	(0.3, 0.6)	(0.5, 0.2)
ϑ_3	(0.4, 0.4)	(0.5, 0.4)	(0.8, 0.1)	(0.7, 0.1)
ϑ_4	(0.8,0.1)	(0.2, 0.7)	(0.4, 0.4)	(0.8, 0.2)
ϑ_5	(0.7, 0.3)	(0. , 0.6)	(0.6, 0.3)	(0.5, 0.2
ϑ_6	(0.9, 0.1)	(0.2, 0.6)	(0.4, 0.3)	(0.3, 0.5)

Table 1(a): IFSS (F_1, C) .

	Big	Very big	Small	Very small	Medium
ϑ_1	(0.4, 0.3)	(0.2, 0.7)	(0.8, 0.2)	(0.6, 0.2)	(0.5, 0.3)
ϑ_2	(0.8, 0.1)	(0.6, 0.1)	(0.3, 0.5)	(0.1, 0.6)	(0.7, 0.2)
ϑ_3	(0.6, 0.2)	(0.4, 0 3)	(0.4, 0.4)	(0.1, 0.5)	(0.7, 0.1)
ϑ_4	(0.9, 0.1)	(0.8, 0.2)	(0.2, 0.6)	(0.1, 0.7)	(0.4, 0.5)
ϑ_5	(0.2, 0.5)	(0.1,0.6)	(0.9, 0.1)	(0.8, 0.1)	(0.7, 0.3)
ϑ_6	(0.3, 0.6)	(0.2, 0.5)	(0.8, 0.1)	(0.6, 0.2)	(0.5, 0.4)

Table 1(b): IFSS (F_2, S) .

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	Very cheap	Cheap	High	Average
ϑ_1	(0.3, 0.5)	(0.4, 0.4)	(0.1, 0.7)	(0.9, 0.1)
ϑ_2	(0.6, 0.2)	(0.5, 0.3)	(0.4, 0.4)	(0.5, 0.2)
ϑ_3	(0.5, 0.4)	(0.6, 0.1)	(0.3, 0.4)	(0.6, 0.1)
ϑ_4	(0.7,0.2)	(0.6, 0.3)	(0.6, 0.2)	(0.3, 0.6)
ϑ_5	(0. , 0.3)	(0.6, 0.2)	(0.5, 0 3)	(0.4, 0.5)
ϑ_6	(0.8, 0.1)	(0.7, 0.1)	(0.7, 0.3)	(0.9, 0.1)

Table 1(c): IFSS (F_3, P) .

Performing " (F_1, C) and (F_2, S) " for the first two IFSS (F_1, C) and (F_2, S) , we get 20 strategies of the type f_{ij} , where

$$f_{ij} = ((\mu_{F_1(a_i)} \land \mu_{F_2(b_j)}), (\lambda_{F_1(a_i)} \lor \lambda_{F_2(b_j)}))$$

for $1 \le i \le 4$ and $1 \le j \le 5$, which are represented in Tables. 2(a) - 2(d). Here meet operation table represent the membership and join operation table explained the non-membership values for each.

$f_{ij} =$	$((\mu_{F_{1}(a)}))$	$\mu_{i} \wedge \mu_{j}$	$F_{2}(b_{j})$),	$(\lambda_{F_1(a_i)})$	$\vee \lambda_{F_2}$	$(b_{j})))$
meet	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}	raw max
ϑ_1	0.3	0.2	0.3	0.3	0.3	0.3
ϑ_2	0.3	0.3	0.3	0.1	0.3	0.3
ϑ_3	0.4	0.4	0.4	.1	0.4	0.4
ϑ_4	0.8	0.8	0.2	0.1	0.8	0.8
ϑ_5	0.2	0.1	0.7	0.7	0.7	0.7
ϑ_6	0.3	0.2	0.8	0.6	0.8	0.8
CD	2	3	1	4	2	
join	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}	raw min
ϑ_1	0.4	0.7	0.4	0.4	0.4	0.4
ϑ_2	0.5	0.5	0.5	0.6	0.5	0.5
ϑ_3	0.4	0.4	0.4	0.5	0.4	0.4
ϑ_4	0.1	0.2	0.6	0.7	0.5	0.1
ϑ_5	0.5	0.6	0.3	0.3	0.3	0.3
ϑ_6	0.6	0.6	0.1	0.2	0.4	0.1
CD	2	4	1	4	2	

Table 2(a): f_{1j} (*for* j=1,2,3,4,5)

meet	f_{21}	f_{22}	f_{23}	f_{24}	f_{25}	raw max
ϑ_1	0.4	0.2	0.4	0.4	0.4	0.4
ϑ_2	0.8	0.6	0.3	0.1	0.7	0.8
ϑ_3	0.5	0.4	0.4	0.1	0.5	0.5
ϑ_4	0.2	0.2	0.2	0.1	0.2	0.2
ϑ_5	0.2	0.1	0.3	0.3	0.3	0.3
ϑ_6	.2	0.2	0.2	0.2	0.2	0.2
CD	1	4	2	3	1	

join	f_{21}	f_{22}	f_{23}	f_{24}	f_{25}	raw min
ϑ_1	0.5	0.7	0.5	0.5	0.5	0.5
ϑ_2	0.1	0.1	0.5	0.6	0.2	0.1
ϑ_3	0.4	0.4	0.4	0.5	0.4	0.4
ϑ_4	0.7	0.7	0.7	0.7	0.7	0.7
ϑ_5	0.6	0.6	0.6	0.6	0.6	0.6
ϑ_6	0.6	0.6	0.6	0.6	0.6	0.6
CD	0	1	0	2	1	

Table 2(b):
$$f_{2j}$$
 (*for* j=1,2,3,4,5)

meet	f_{31}	f_{32}	f_{33}	f_{34}	f_{35}	raw max
ϑ_1	0.4	0.2	0.6	0.6	0.5	0.6
ϑ_2	0.3	0.3	0.3	0.1	0.3	0.3
ϑ_3	0.6	0.4	0.4	0.1	0.7	0.7
ϑ_4	0.4	0.4	0.2	0.1	0.4	0.4
ϑ_5	0.2	0.1	0.6	0.6	0.6	0.6
ϑ_6	0.3	0.2	0.4	0.6	0.4	0.6
CD	4	4	3	3	2	
join	f_{31}	f_{32}	f_{33}	f_{34}	f_{35}	raw min
join ϑ1	<i>f</i> ₃₁ 0.3	<i>f</i> ₃₂ 0.7	f ₃₃ 0.2	<i>f</i> ₃₄ 0.2	<i>f</i> ₃₅ 0.3	raw min 0.2
join ϑ_1 ϑ_2	<i>f</i> ₃₁ 0.3 0.6	<i>f</i> ₃₂ 0.7 0.6	<i>f</i> ₃₃ 0.2 0.6	<i>f</i> ₃₄ 0.2 0.6	<i>f</i> ₃₅ 0.3 0.6	raw min 0.2 0.6
join ϑ_1 ϑ_2 ϑ_3	f_{31} 0.3 0.6 0.2	f_{32} 0.7 0.6 0.3	f_{33} 0.2 0.6 0.4	f_{34} 0.2 0.6 0.5	f_{35} 0.3 0.6 0.1	raw min 0.2 0.6 0.1
join ϑ_1 ϑ_2 ϑ_3 ϑ_4	f_{31} 0.3 0.6 0.2 0.4	f_{32} 0.7 0.6 0.3 0.4	f_{33} 0.2 0.6 0.4 0.6	f_{34} 0.2 0.6 0.5 0.7	f_{35} 0.3 0.6 0.1 0.5	raw min 0.2 0.6 0.1 0.4
join ϑ_1 ϑ_2 ϑ_3 ϑ_4 ϑ_5	f_{31} 0.3 0.6 0.2 0.4 0.5	f_{32} 0.7 0.6 0.3 0.4 0.6	f_{33} 0.2 0.6 0.4 0.6 0.3	f_{34} 0.2 0.6 0.5 0.7 0.3	f_{35} 0.3 0.6 0.1 0.5 0.3	raw min 0.2 0.6 0.1 0.4 0.3
join ϑ_1 ϑ_2 ϑ_3 ϑ_4 ϑ_5 ϑ_6	$\begin{array}{c} f_{31} \\ 0.3 \\ 0.6 \\ 0.2 \\ 0.4 \\ 0.5 \\ 0.6 \end{array}$	$\begin{array}{c} f_{32} \\ 0.7 \\ 0.6 \\ 0.3 \\ 0.4 \\ 0.6 \\ 0.5 \end{array}$	f_{33} 0.2 0.6 0.4 0.6 0.3 0.3	$\begin{array}{c} f_{34} \\ 0.2 \\ 0.6 \\ 0.5 \\ 0.7 \\ 0.3 \\ 0.3 \end{array}$	f_{35} 0.3 0.6 0.1 0.5 0.3 0.4	raw min 0.2 0.6 0.1 0.4 0.3 0.3

Table 2(c): f_{3j} (*for* j=1,2,3,4,5)

meet	f_{41}	f_{42}	f_{43}	f_{44}	f_{45}	raw max
ϑ_1	0.4	0.2	0.8	0.6	0.5	0.8
ϑ_2	0.5	0.5	0.3	0.1	.5	0.5
ϑ_3	0.6	0.	0.4	0.1	0.7	0.7
ϑ_4	0.8	0.8	0.2	0.1	0.4	0.8
ϑ_5	0.2	0.1	0.5	0.5	0.5	0.5
ϑ_6	0.3	0.2	0.3	0.3	0.3	0.3
CD	3	4	3	4	2	
join	f_{41}	f_{42}	f_{43}	f_{44}	f_{45}	raw min
join ϑ_1	f_{41} 0.3	<i>f</i> ₄₂ 0.7	f ₄₃	f_{44} 0.2	f_{45} 0.3	raw min 0.2
$\frac{\text{join}}{\vartheta_1}$	f_{41} 0.3 0.2	<i>f</i> ₄₂ 0.7 0.2	f_{43} 0.2 0.5	<i>f</i> ₄₄ 0.2 0.6	f_{45} 0.3 0.2	raw min 0.2 0.2
join ϑ_1 ϑ_2 ϑ_3	f_{41} 0.3 0.2 0.2	f_{42} 0.7 0.2 0.3	f_{43} 0.2 0.5 0.4	f_{44} 0.2 0.6 0.5	f_{45} 0.3 0.2 0.1	raw min 0.2 0.2 0.1
$\begin{array}{c} \text{join} \\ \hline \vartheta_1 \\ \vartheta_2 \\ \vartheta_3 \\ \vartheta_4 \end{array}$	$\begin{array}{c} f_{41} \\ 0.3 \\ 0.2 \\ 0.2 \\ 0.2 \\ 0.2 \end{array}$	$\begin{array}{c} f_{42} \\ 0.7 \\ 0.2 \\ 0.3 \\ 0.2 \end{array}$	$\begin{array}{c} f_{43} \\ \hline 0.2 \\ 0.5 \\ 0.4 \\ 0.6 \end{array}$	f_{44} 0.2 0.6 0.5 0.7	$\begin{array}{c} f_{45} \\ 0.3 \\ 0.2 \\ 0.1 \\ 0.5 \end{array}$	raw min 0.2 0.2 0.1 0.2
$\begin{array}{c} \text{join} \\ \vartheta_1 \\ \vartheta_2 \\ \vartheta_3 \\ \vartheta_4 \\ \vartheta_5 \end{array}$	$\begin{array}{c} f_{41} \\ 0.3 \\ 0.2 \\ 0.2 \\ 0.2 \\ 0.5 \end{array}$	$\begin{array}{c} f_{42} \\ 0.7 \\ 0.2 \\ 0.3 \\ 0.2 \\ 0.6 \end{array}$	$\begin{array}{c} f_{43} \\ 0.2 \\ 0.5 \\ 0.4 \\ 0.6 \\ 0.2 \end{array}$	$\begin{array}{c} f_{44} \\ 0.2 \\ 0.6 \\ 0.5 \\ 0.7 \\ 0.2 \end{array}$	$\begin{array}{c} f_{45} \\ 0.3 \\ 0.2 \\ 0.1 \\ 0.5 \\ 0.3 \end{array}$	raw min 0.2 0.2 0.1 0.2 0.2 0.2
$\begin{array}{c} \text{join} \\ \hline \vartheta_1 \\ \vartheta_2 \\ \vartheta_3 \\ \vartheta_4 \\ \vartheta_5 \\ \vartheta_6 \end{array}$	$\begin{array}{c} f_{41} \\ 0.3 \\ 0.2 \\ 0.2 \\ 0.2 \\ 0.5 \\ 0.6 \end{array}$	$\begin{array}{c} f_{42} \\ 0.7 \\ 0.2 \\ 0.3 \\ 0.2 \\ 0.6 \\ 0.5 \end{array}$	$\begin{array}{c} f_{43} \\ 0.2 \\ 0.5 \\ 0.4 \\ 0.6 \\ 0.2 \\ 0.5 \end{array}$	$\begin{array}{c} f_{44} \\ 0.2 \\ 0.6 \\ 0.5 \\ 0.7 \\ 0.2 \\ 0.5 \end{array}$	$\begin{array}{c} f_{45} \\ 0.3 \\ 0.2 \\ 0.1 \\ 0.5 \\ 0.3 \\ 0.5 \end{array}$	raw min 0.2 0.2 0.1 0.2 0.2 0.2 0.5
$\begin{array}{c} \text{join} \\ \\ \vartheta_1 \\ \\ \vartheta_2 \\ \\ \vartheta_3 \\ \\ \vartheta_4 \\ \\ \vartheta_5 \\ \\ \vartheta_6 \\ \text{CD} \end{array}$	$\begin{array}{c} f_{41} \\ 0.3 \\ 0.2 \\ 0.2 \\ 0.2 \\ 0.5 \\ 0.6 \\ 3 \end{array}$	$\begin{array}{c} f_{42} \\ 0.7 \\ 0.2 \\ 0.3 \\ 0.2 \\ 0.6 \\ 0.5 \\ 3 \end{array}$	$\begin{array}{c} f_{43} \\ 0.2 \\ 0.5 \\ 0.4 \\ 0.6 \\ 0.2 \\ 0.5 \\ 3 \end{array}$	$\begin{array}{c} f_{44} \\ 0.2 \\ 0.6 \\ 0.5 \\ 0.7 \\ 0.2 \\ 0.5 \\ 3 \end{array}$	$\begin{array}{c} f_{45} \\ 0.3 \\ 0.2 \\ 0.1 \\ 0.5 \\ 0.3 \\ 0.5 \\ 3 \end{array}$	raw min 0.2 0.2 0.1 0.2 0.2 0.2 0.5

Table 2(d): <i>f</i>	$f_{1:}$ (for f	i = 1.2	.3.4	.5
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In each table CD stand for comparison data, which we determine by comparing the raw min and raw max column with the other column entries for membership and non-membership values respectively.

The parameters $Q = \{f_{11}, f_{13}, f_{15}, f_{21}, f_{23}, f_{25}\}$ are then computed by using the comparison data for row maxima and column minima. Here we choose those of the strategies which have comparison value zero, one and two. Let us introduce the new resultant IFSS by (R_1, Q) , that's represented in Table 3.

f_{11}	f_{13}	f_{15}	f_{21}	f_{23}	f_{25}
(0.3, 0.4)	(0.3, 0.4)	(0.3, 0.4)	(0.4, 0.5)	(0.4, 0.5)	(0.4, 0.5)
(0.3, 0.5)	(0.3, 0.5)	(0.3, 0.5)	(0.8, 0.1)	(0.3, 0.5)	(0.7, 0.2)
(0.4, 0.4)	(0.4, 0.4)	(0.4, 0.4)	(0.5, 0.4)	(0.4, 0.4)	(0.5, 0.4)
(0.8, 0.1)	(0.2, 0.6)	(0.4, 0.5)	(0.2, 0.7)	(0.2, 0.7)	(0.2, 0.7)
(0.2, 0.5)	(0.7, 0.3)	(0.7, 0.3)	(0.2, 0.6)	(0.3, 0.6)	(0.3, 0.6)
(0.3, 0.6)	(0.8, 0.1)	(0.5, 0.4)	(0.2, 0.6)	(0.2, 0.6)	(0.2, 0.6)

Table 3: Resultant IFSS (R_1, Q) .

Finally Performing the same logical formula for " (R_1, Q) " and " (F_3, P) " we achive 24 new strategies of the type d_{ij} , where

$$d_{ij} = ((\mu_{R_1(a_i)} \land \mu_{F_3(b_j)}), (\lambda_{R_1(a_i)} \lor \lambda_{F_3(b_j)}))$$

for

 $1 \le i \le 6$ and $1 \le j \le 4$, which are represented in Tables. 4(a) - 4(f).

meet	d_{11}	d_{12}	<i>d</i> ₁₃	d_{14}	raw max
ϑ_1	0.3	0.3	0.1	0.3	0.3
ϑ_2	0.3	0.3	0.3	0.3	0.3
ϑ_3	0.4	0.4	0.3	0.4	0.4
ϑ_4	0.7	0.6	0.6	0.3	0.7
ϑ_5	0.2	0.2	0.2	0.2	0.2
ϑ_6	0.3	0.3	0.3	0.3	0.3
CD	0	1	3	1	

join	d_{11}	d_{12}	d_{13}	d_{14}	raw min
ϑ_1	0.5	0.4	0.7	0.4	0.4
ϑ_2	0.5	0.5	0.5	0.5	0.5
ϑ_3	0.4	0.4	0.4	0.4	0.4
ϑ_4	0.2	0.3	0.2	0.6	0.2
ϑ_5	0.5	0.5	0.5	0.5	0.5
ϑ_6	0.6	0.6	0.6	0.6	0.6
CD	1	1	1	1	

Table 4(a):
$$d_{1i}$$
 (for j = 1,2,3,4).

meet	d_{21}	<i>d</i> ₂₂	<i>d</i> ₂₃	<i>d</i> ₂₄	raw max
ϑ_1	0.3	0.3	0.1	0.3	0.3
ϑ_2	0.3	0.3	0.3	0.3	0.3
ϑ_3	0.4	0.4	0.3	0.4	0.4
ϑ_4	0.2	0.2	0.2	0.2	0.2
ϑ_5	0.6	0.6	0.5	0.4	0.
ϑ_6	0.8	0.7	0.7	0.8	0.8
CD	0	1	4	1	

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join	d_{21}	d_{22}	<i>d</i> ₂₃	d_{24}	raw min	join	d_{41}	d_{42}	d_{43}	$d_{_{44}}$	raw min
ϑ_1	0.5	0.4	0.7	0.4	0.4	ϑ_1	0.5	0.5	0.7	0.5	0.5
ϑ_2	0.5	0.5	0.5	0.5	0.5	ϑ_2	0.2	0.3	0.4	0.2	0.2
θa	0.4	0.4	0.4	0.4	0.4	ϑ_3	0.4	0.4	0.4	0.4	0.4
194	0.6	0.6	0.6	0.	0.6	ϑ_4	0.7	0.7	0.7	0.7	0.7
19_	0.3	0.3	0.3	0.5	0.3	ϑ_5	0.6	0.6	0.6	0.6	0.6
0	0.5	0.5	0.2	0.5	0.1	ϑ_6	0.6	0.6	0.6	0.6	0.6
v_6	0.1	0.1	0.5	0.1	0.1	CD	0	1	2	0	
CD	1	0	2	1				-	-	°	
	Table	4(b): <i>d</i> ₂	_j (<i>for</i> j	=1,2,3,	4).		Table	4(d): d_{4j}	(for j = 1)	,2,3,4).	
meet	<i>d</i> ₃₁	<i>d</i> ₃₂	<i>d</i> ₃₃	d_{34}	raw max	meet	d_{51}	d_5	$d_{52} d_{53}$	$_{3}$ d_{54}	raw max
ϑ_1	0.3	0.3	0.1	0.3	0.3	ϑ_1	0.3	0.	4 0.1	0.4	0.4
ϑ_2	0.3	0.3	0.3	0.3	0.3	ϑ_2	0.3	0.	3 0.3	0.3	0.3
ϑ_3	0.4	0.4	0.3	0.4	0.4	ϑ_3	0.4	0	4 0.3	0.4	0.4
ϑ_4	0.4	0.4	0.4	0.3	0.4	ϑ_4	0.2	0.	2 0.2	0.2	0.2
ϑ_5	0.6	0.6	0.5	0.4	0.6	ϑ_5	0.3	0.	3 0.3	0.3	0.3
ϑ_6	0.5	0.5	0.5	0.5	0.5	ϑ_6	0.2	0.	2 0.2	0.2	0.2
CD	0	0	3	2		CD	1	0	2	0	
join	d_{31}	d_{32}	<i>d</i> ₃₃	$d_{_{34}}$	raw min	join	d_{51}	d_{52}	d_{53}	d_{54}	raw min
19.	0.5	0.4	0.7	0.4	0.4	ϑ_1	0.5	0.5	0.7	0.5	0.5
ϑ_2	0.5	0.5	0.5	0.5	0.5	ϑ_2	0.5	0.5	0.5	0.5	0.5
ϑ_3	0.4	0.4	0.4	0.4	0.4	ϑ_3	0.4	0.4	0.4	0.4	0.4
ϑ_4	0.5	0.5	0.5	0.6	0.5	ϑ_4	0.7	0.7	0.7	0.7	0.7
ϑ_5	0.3	0.3	0.3	0.5	0.3	ϑ_5	0.6	0.6	0.6	0.6	0.6
ϑ_6	0.4	0.4	0.4	0.4	0.4	ϑ_6	0.6	0.6	0.6	0.6	0.6
CD	1	0	0	2		CD	0	0	1	0	
	Table	4(c): <i>d</i> ₃	$_{j}$ (for j	=1,2,3,4	4).		Table	$4(e): d_{5j}$ (for $j=1$,2,3,4).	
	<i>d</i>	d_{12}	d_{42}	<i>d</i>		meet	$d_{_{61}}$	d_{62}	<i>d</i> ₆₃	$d_{_{64}}$	raw max
$\frac{\vartheta_1}{\vartheta_1}$	0.3	0.4	0.1	0.4	0.4	ϑ_1	0.3	0.4	0.1	0.4	0.4
ϑ_2	0.6	0.5	0.4	0.5	0.6	ϑ_2	0.6	0.5	0.4	0.5	0.6
ϑ_3	0.5	0.5	0.3	0.5	0.5	ϑ_3	0.5	0.5	0.3	0.5	0.5
ϑ_4	0.2	0.2	0.2	0.2	0.2	ϑ_4	0.2	0.2	0.2	0.2	0.2
ϑ_5	0.2	0.2	0.2	0.2	0.2	ϑ_5	0.3	0.3	0.3	0.3	0.3
ϑ_6	0.2	0.2	0.2	0.2	0.2	ϑ_6	0.2	0.2	0.2	0.2	0.2
CD	1	1	3	1		CD	1	1	3	1	

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join	<i>d</i> ₆₁	d_{62}	<i>d</i> ₆₃	$d_{_{64}}$	raw mir
ϑ_1	0.5	0.5	0.7	0.5	.5
ϑ_2	0.2	0.3	0.4	0.2	0.2
ϑ_3	0.4	0.4	0.4	0.4	0.4
ϑ_4	0.7	0.7	0.7	0.7	0.7
ϑ_5	0.6	0.6	0.6	0.6	0.6
ϑ_6	0.6	0.6	0.6	0.6	0.6
CD	0	1	2	0	

Table 4(f): d_{6i} (for j = 1,2,3,4).

On basis of the previous algorithm the final resultant IFSS is view in Table 5. Here strategies comparison values are zero and one.

MB	d_{11}	d_{21}	d_{31}	<i>d</i> ₃₂	<i>d</i> ₅₂	d_{54}
ϑ_1	0.3	0.3	0.3	0.3	0.4	0.4
ϑ_2	0.3	0.3	0.3	0.3	0.3	0.3
ϑ_3	0.4	0.4	0.4	0.4	0.4	0.4
ϑ_4	0.7	0.2	0.4	0.4	0.2	0.2
ϑ_5	0.2	0.6	0.6	0.6	0.3	0.3
ϑ_6	0.3	0.8	0.5	0.5	0.2	0.2
NMB	d_{11}	d_{21}	d_{31}	d_{32}	d_{52}	d_{54}
ϑ_1	0.5	0.5	0.5	0.4	0.5	0.5
ϑ_2	0.5	0.5	0.5	0.5	0.5	0.5
ϑ_3	0.4	0.4	0.4	0.4	0.4	0.4
ϑ_{A}			0.5	0.5	07	07
т	0.2	0.6	0.5	0.5	0.7	0.7
ϑ_5	0.2 0.5	0.6 0.3	0.5 0.3	0.5	0.7	0.6

Table 5: Resultant IFSS.

Tables. 6(a)-6(b) illustrates the comparison-table of the above resultant IFSS.

MV	ϑ_1	ϑ_2	ϑ_3	ϑ_4	ϑ_5	ϑ_6
ϑ_1	6	6	2	3	3	3
ϑ_2	4	6	0	4	4	4
ϑ_3	6	6	6	5	3	3
ϑ_4	3	3	3	6	1	3
ϑ_5	3	5	3	5	6	4
ϑ_6	4	4	3	5	2	6

 Table 6(a): Comparison table for membership values (MV).

NMV	ϑ_1	ϑ_2	ϑ_3	ϑ_4	ϑ_5	ϑ_6
ϑ_1	6	6	2	3	3	3
ϑ_2	4	6	0	4	4	4
ϑ_3	6	6	6	5	3	3
ϑ_4	3	3	3	6	1	3
ϑ_5	3	5	3	5	6	4
ϑ_6	4	4	3	5	2	6

Table 6(b): Comparison table for membership values (NMV).

And, finally we calculate the row-sum (RS), column-sum (CS). The computation table is demonstrated in Table 6(c).

MV	RS	CS	Diff	NMV	RS	CS	Diff
ϑ_1	23	26	-3	ϑ_1	25	26	-1
ϑ_2	22	30	-8	ϑ_2	22	28	-6
ϑ_3	29	17	12	ϑ_3	31	14	17
ϑ_4	19	28	-9	ϑ_4	14	31	-17
ϑ_5	26	19	7	ϑ_5	27	19	8
ϑ_6	24	23	1	ϑ_6	23	24	-1

Table 6(c): Difference of RS and CS for MVand NMV.

From the above computation, we observe that for k=3 the difference is maximum, thus the decision is in favors of selecting \mathcal{P}_3 .

Conclusion

In our present work we deliver an appliance of IFSS theory in object determination problem. For the convenience of our work, we first select some parameters like color, size and price for the selected objects and define them with the concept of IIFS in Tables. 1(a) - 1(c). Sequentially using "and" operation and comparison data for the three IIFSs, we get a resultant IIFS. Finally, by formatting and analyzing a comparison table for the resultant IFSS we ascertain that the desired object is \mathcal{P}_3 .

References

- Atanassov K. Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*. 1986; 20(1): 87-96.
- Atanassov K. Operators over interval valued intuitionistic fuzzy sets. *Fuzzy Sets and Systems*. 1994; 64(2): 159-174.
- Gau WL and Buehrer DJ. Vague sets, IEEE Trans. *System Man Cybernet*. 1993; 23 (2): 610-614.
- Islam MS, Hossain MS and Asaduzzaman M. Level separation on Intuitionistic fuzzy T1 spaces. J. Bangladesh Acad. Sci 2018; 42(1): 73-85.
- Mahbub MA, Hossain MS and Hossain MA. On Qcompactness in Intuitionistic Fuzzy topological spaces. J. Bangladesh Acad. Sci. 2019; 43(2): 197-230.
- Maji PK, Biswas R and Roy AR. Fuzzy soft sets. J. *Fuzzy Math.* 2001; 9(3): 589-602.
- Maji PK, Biswas R and Roy AR. Soft set theory. *Comput. Math. Appl.* 2003; 45(4-5): 555-562.

- Molodtsov D. Soft set theory-first results. *Comput. Math. Appl.* 1999; 37: 19-31.
- Pawlak Z. Rough sets, Internat. J. Inform. Comput. Sci. 1982; 11: 341-356.
- Pawlak Z. Hard set and soft sets, ICS Research Report. Ins. Comput. Sci. Poland. 1994
- Prade H and Dubois D. Fuzzy Sets and Systems Theory and Applications. *Academic Press, London.* 1980.
- Roy AR and Maji PK. A fuzzy soft set theoretic approach to decision making problems. J. *Comput. Appl. Math.* 2007; 203(2): 412-418.
- Zadeh LA. Fuzzy sets. Infor Control. 1965; 8: 338-353.
- Zimmerman HJ. Fuzzy Set Theory and Its applications. *Kluwer Academic Publishers, Boston.* 1996.