

# Application of Picture Fuzzy Soft Relations in Multi- attribute Decision Making

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**Abstract :** In this paper, we first define picture fuzzy soft sets (PFSS) and study some of their relevant operations such as subset, equal, complement, AND, OR... and so on. we investigate some theorems on picture fuzzy soft sets based on union and intersection with counter examples. Also we proved a necessary and sufficient condition for the dual laws of PFSS theory. Finally, we then introduce an algorithm based on relational picture fuzzy soft matrix to solve decision making problems.

**Key words:** fuzzy set, soft set, fuzzy soft set, picture fuzzy soft set, subset, equal, AND, OR, complement, dual law, decision making.

## 1 Introduction

A fuzzy set was first introduced by Zadeh [23] and then the fuzzy sets have been used in their consideration of classical mathematics. Yuan et al. [22] introduced the concept of fuzzy subgroup with thresholds. A fuzzy subgroup with thresholds  $\lambda$  and  $\mu$  is also called a  $(\lambda, \mu)$ -fuzzy subgroup. A. Solairaju and R. Nagarajan introduced the concept of structures of Q-fuzzy groups [19]. A. Solairaju and R. Nagarajan studied some structural properties of upper Q-fuzzy index order, with upper Q-fuzzy subgroups [20]. Such inaccuracies are associated with the membership function that belongs to  $[0, 1]$ . Through membership function, we obtain information which makes possible for us to reach the conclusion. The fuzzy set theory becomes a strong area of making observations in different areas like medical science, social sciences, engineering, management sciences, artificial intelligence, robotics, computer networks, decision making and so on. Due to unassociated sorts of unpredictability occurring in different areas of life like economics, engineering, medical sciences, management sciences, psychology, sociology, decision making and fuzzy set as noted and often effective mathematical instruments have been offered to make, be moving in and grip those unpredictability. Since the establishment of fuzzy set, several extensions have been made such as Atanassov's ([3], [4], [5], [6]) work on

intuitionistic fuzzy set (IFSs) was quite remarkable as he extended the concept of FSs by assigning non-membership degree say "N(x)" along with membership degree say "P(x)" with condition that  $0 \leq P(x) + N(x) \leq 1$ . Strengthening the concept IFS suggest pythagorean fuzzy sets which somehow enlarge the space of positive membership and negative membership by introducing some new condition that  $0 \leq P^2(x) + N^2(x) \leq 1$ . Molodtsov [14] introduced the concept of soft sets that can be seen as a newmathematical theory for dealing with uncertainty. The soft set theory has been applied to many different fields with great success. Maji.et.al. ([8],[9][10]) worked on theoretical study of soft sets in detail, and presented an application of soft set in the decision making problem using the reduction of rough sets. *N*-picture fuzzy soft sets studied in [12,13].Recently, Cuong [7] proposed picture fuzzy set (PFS) and investigated the some basic operations and properties of PFS. The picture fuzzy set is characterized by three functions expressing the degree of membership, the degree of neutral membership and the degree of non-membership. The only constraint is that the sum of the three degrees must not exceed 1. Basically, PFS based models can be applied to situations requiring human opinions involving more answers of types: yes, abstain, no, refusal, which cant be accurately expressed in the traditional FS and IFS. Until now, some progress has been made in the research of the PFS theory. Singh [17] investigated the correlation coefficients for picture fuzzy set and apply the correlation coefficient to clustering analysis with picture fuzzy information. Son [18] introduce several novel fuzzy clustering algorithms on the basis of picture fuzzy sets and applications to time series forecasting and weather forecasting. In this paper,we Define picture fuzzy soft sets (PFSS) and study some of their relevant operations such as subset,equal, complement, AND,OR... and so on.we investigate some theorems on picture fuzzy soft sets based on union and intersection with counter examples. Also we proved a necessary and sufficent condition for the dual laws of PFSS theory.Finaly, we then introduce an algorithm based on relational picture fuzzy soft matrix to solve decision making problems.

## 2 Preliminaries and Basic Concepts

### 2.1 Definition

Let the universal set be  $R \neq \phi$ . Then  $A = \{ \langle r, P_{A(r)} \rangle / r \in R \}$  is said to be a fuzzy set of  $R$ , where  $P_A : U \rightarrow [0, 1]$ . is said to be the membership degree of  $r$  in  $R$ .

### 2.2 Example

Let  $R = \{r_1, r_2, r_3, r_4, r_5\}$  be the reference set of students. Let  $\tilde{A}$  be the fuzzy set of "smart students" where 'smart' is fuzzy term.  $\tilde{A} = \{ \langle r_1, 0.1 \rangle, \langle r_2, 0.4 \rangle, \langle r_3, 0.7 \rangle, \langle r_4, 1 \rangle, \langle r_5, 0.9 \rangle \}$ . Here  $\tilde{A}$  indicates that the smartness of  $r_1$  is 0.1 and so on.

### 2.3 Definition

A pair  $(\delta, A)$  is called soft set over  $R$ , where  $F$  is a mapping given by  $F : A \rightarrow P(R)$ .

### 2.4 Example

Suppose  $R = \{h_1, h_2, h_3, h_4, h_5, h_6\}$  be the the set of six houses and  $E = \{ \text{Expensive}(e_1), \text{Beautiful}(e_2), \text{Wooden}(e_3), \text{Cheap}(e_4) \}$  then the soft set  $(\delta, E)$  is  $(\delta, E) = \{ \{h_2, h_4\} \{h_1, h_3\}, \{h_3, h_4, h_5\}, \{h_1, h_3, h_5\} \}$  where each approximation has two parts

- (i) a predicate,  $P$ ;
- (ii) an approximate value set  $V$ .

$R$	$Expensive(e_1)$	$Beautiful(e_2)$	$Wooden(e_3)$	$Cheap(e_4)$
$h_1$	0	1	0	1
$h_2$	1	0	0	0
$h_3$	0	1	1	1
$h_4$	1	0	1	0
$h_5$	0	0	1	1
$h_6$	0	0	0	0

thus, a sof set  $(\delta, E) = \{P_1 = V_1, P_2 = V_2, P_3 = V_3, \dots, P_n = V_n\}$ .

## 2.5 Definition

Let  $I^R$  denote the set of all fuzzy sets on  $X$  and  $A \subseteq E$ . A pair  $(\delta, A)$  is called fuzzy soft set over  $R$ , where  $\delta : A \rightarrow I^R$ . that is, for each  $a \in A$ ,  $\delta_a : \rightarrow I^R$  is the fuzzy set on  $R$ .

## 2.6 Example

Let  $R = \{r_1, r_2, r_3, r_4, r_5\}$  be a universal set and  $E = \{e_1, e_2, e_3, e_4, e_5\}$  be a set of parameters. If  $A = \{e_1, e_2, e_4\} \subseteq E$ .  $P_A(e_1) = \{0.2/r_2, 0.3/r_4, \}$ ,  $P_A(e_2) = R$   $P_A(e_4) = \{0.5/r_1, 0.7/r_3, 0.9/r_5\}$  then the fuzzy soft set  $\delta_A$  is defined as  $\delta_A = \{r_1, (0.2/r_2, 0.3/r_4), (r_2, U), (r_4, (0.5/r_1, 0.7/r_3, 0.9/r_5))\}$ .

## 2.7 Definition

Let the universe set be  $R \neq \phi$ . Then the set  $A = \{ \langle r, P_{A(r)}, I_{A(r)}, N_{A(r)} \rangle / r \in R \}$  is said to be a picture fuzzy set of  $R$ , where  $P_A : R \rightarrow [0, 1]$ ,  $I_A : R \rightarrow [0, 1]$ ,  $N_A : R \rightarrow [0, 1]$ . are said to be the degree of  $r$  in  $R$  and the positive membership degree of  $r$  in  $R$ , and the neutral membership degree of  $r$  in  $R$ , and the negative membership degree of  $r$  in  $R$  respectively. Also  $P_{(A)}, I_{(A)}, N_{(A)}$  satisfy the following condition:  $(\forall r \in R) (0 \leq P_{A(r)} + I_{A(r)} + N_{A(r)} < 1)$ . Then for  $r \in R$ ,  $\pi_{A(r)} = 1 - \{P_{A(r)} + I_{A(r)} + N_{A(r)}\}$  could be called the degree of refusal membership of  $r$  in  $R$ . Clearly, if  $(r \in R)$ ,  $\pi_{A(r)} = 0$ , then  $A$  will be generated to be a standard intuitionistic fuzzy set. If  $(\forall r \in R), I_{A(r)} = 0$  and  $\Pi_{A(r)} = 0$ , then  $A$  will be generated to be a classical fuzzy set. Let  $\Pi_{A(r)}$  denote the set of all fuzzy sets of  $R$ . For the sake of simplicity picture fuzzy set is denoted by PFS.

## 2.8 Example

Basically, the model picture fuzzy set may be adequate in situations when we face human opinions involving more answers of type: (i) Yes (ii) abstain (iii) No (iv) Refusal. Voting can be a good example of such a situation as the human voters may be divided into four groups of those who: (i) Vote for (ii) abstain (iii) Vote against (iv) Refusal of the voting.

## 2.9 Definition

For  $A, B \in PF(R)$ , define (i)  $A \subseteq B \iff P_{A(r)} \leq P_{B(r)}, I_{A(r)} \leq I_{B(r)}$  and  $N_{A(r)} \leq N_{B(r)}$ .

(ii)  $A = B \iff A \subseteq B$  and  $B \subseteq A$ .

(iii)  $A \cup B = \{(r, \max\{P_{A(r)}, P_{B(r)}\}), \min\{I_{A(r)}, I_{B(r)}\}, \min\{N_{A(r)}, N_{B(r)}\}\}/r \in R\}$ .

(iv)  $A \cap B = \{(r, \min\{P_{A(r)}, P_{B(r)}\}), \min\{I_{A(r)}, I_{B(r)}\}, \max\{N_{A(r)}, N_{B(r)}\}\}/r \in R\}$ .

(v)  $A^C = \{(r, N_{A(r)}, I_{A(r)}, P_{A(r)})/r \in R\}$ .

## 2.10 Proposition

Let  $A, B, C \in PF(R)$ . Then (i) If  $A \subseteq B$  and  $B \subseteq C$ , then  $A \subseteq C$

(ii)  $(A^C)^C = A$

(iii) Operations  $\cap$  and  $\cup$  are commutative, associative and distributive.

(iv) Operations  $\cap$  and  $\cup$  satisfy demorgons Laws.

## 3 Properties of Picture Fuzzy Soft set

In this section, we study the concept of PFSS and define some relevant operation on a PFSS, namely subset, equal, complement, AND, OR and so on. Now we propose the definition of a PFSS and we give an illustrative example it.

### 3.1 Definition

Let  $R$  be an initial universe set and  $E$  a set of parameters. By a picture fuzzy soft set (PFSS) over  $R$  we mean a pair  $(\delta, A)$  where  $A \subseteq E$  and  $\delta$  is a mapping given by  $\delta : A \rightarrow PF(R)$ .

### 3.2 Example

Consider a PFSS  $(\delta, A)$  over  $R$ , where  $R = \{h_1, h_2, h_3, h_4\}$  is the set of four cases under consideration of a decision making to purchase, and  $A = \{e_1, e_2, e_3\}$  is the set of parameters where  $e_1$  stands for the parameter "Cheap"  $e_2$  stu-

dents for the parameter "Beautiful"  $e_3$  students for the parameter "Good location" the PFSS  $(\delta, A)$  describes the "attractiveness of the house" to this decision maker. suppose that

$R$	$Cheap(e_1)$	$Beautiful(e_2)$	$Goodlocation(e_3)$
$h_1$	(0.6, 0.3, 0.1)	(0.3, 0.5, 0.2)	(0.7, 0.5, 0.4)
$h_2$	(0.1, 0.4, 0.6)	(0.3, 0.4, 0.5)	(0.1, 0.7, 0.9)
$h_3$	(0.3, 0.7, 0.9)	(0.4, 0.6, 0.7)	(0.2, 0.5, 0.7)
$h_4$	(0.2, 0.5, 0.8)	(0.5, 0.7, 0.9)	(0.3, 0.5, 0.7)

For convence of explanation ,we can also represent PFSS  $(\delta, A)$  which is described in the above in matrix form as follows:

$$(\delta, A) = \begin{matrix} & e_1 & e_2 & e_3 \\ \begin{matrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{matrix} & \left( \begin{matrix} (0.6, 0.3, 0.1) & (0.3, 0.5, 0.2) & (0.7, 0.5, 0.4) \\ (0.1, 0.4, 0.6) & (0.3, 0.4, 0.5) & (0.1, 0.7, 0.9) \\ (0.3, 0.7, 0.9) & (0.4, 0.6, 0.7) & (0.2, 0.5, 0.7) \\ (0.2, 0.5, 0.8) & (0.5, 0.7, 0.9) & (0.3, 0.5, 0.7) \end{matrix} \right) \end{matrix}$$

### 3.3 Definition

Let  $(\delta, A)$  and  $(\Delta, B)$  be two PFSS's over  $U$ . Then  $(\delta, A)$  is called picture fuzzy soft subset of  $(\Delta, B)$ , denoted by  $(\delta, A) \subseteq (\Delta, B)$  if

- (i)  $A \subseteq B$  and
- (ii)  $F(e) \subseteq G(e)$  for all  $e \in A$ .

### 3.4 Example

Let  $U = \{C_1, C_2, C_3, C_4, C_5\}$  and  $E = \{e_1, e_2, e_3, e_4, e_5, e_6\}$ . Suppose  $(\delta, A)$  and  $(\Delta, B)$  are two PFSS's over  $U$  given by  $A = \{e_1, e_2, e_3\}$  and  $B = \{e_1, e_2, e_4, e_5\}$ .

$$(\delta, A) = \begin{matrix} & e_1 & e_2 & e_3 \\ \begin{matrix} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \end{matrix} & \left( \begin{matrix} (0.3, 0.2, 0.1) & (0.2, 0.7, 0.3) & (0.1, 0.5, 0.1) \\ (0.2, 0.2, 0.3) & (0.8, 0.6, 0.1) & (0.1, 0.6, 0.7) \\ (0.1, 0.3, 0.6) & (0.7, 0.3, 0.2) & (0.2, 0.3, 0.1) \\ (0.3, 0.1, 0.2) & (0.3, 0.1, 0.5) & (0.3, 0.7, 0.4) \\ (0.2, 0.1, 0.6) & (0.2, 0.3, 0.7) & (0.5, 0.6, 0.2) \end{matrix} \right) \end{matrix}$$

$$(\Delta, B) = \begin{matrix} & e_1 & e_2 & e_4 & e_5 \\ \begin{matrix} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \end{matrix} & \left( \begin{array}{cccc} (0.6, 0.2, 0.1) & (0.1, 0.2, 0.4) & (0.1, 0.7, 0.6) & (0.7, 0.5, 0.2) \\ (0.5, 0.3, 0.2) & (0.2, 0.4, 0.6) & (0.2, 0.7, 0.5) & (0.1, 0.2, 0.3) \\ (0.1, 0.3, 0.2) & (0.3, 0.0, 0.7) & (0.3, 0.2, 0.1) & (0.3, 0.5, 0.2) \\ (0.1, 0.0, 0.7) & (0.3, 0.7, 0.6) & (0.1, 0.6, 0.2) & (0.7, 0.3, 0.8) \\ (0.0, 0.3, 0.1) & (0.1, 0.2, 0.3) & (0.5, 0.7, 0.2) & (0.1, 0.3, 0.5) \end{array} \right) \end{matrix}$$

then  $\delta_A$  is picture fuzzy soft subset of  $\Delta_B$ .

### 3.5 Definition

Two PFS sets  $\delta_A$  and  $\Delta_B$  over  $U$  are called to be picture fuzzy softset equal, if and only if  $\delta_A$  is a picture fuzzy soft subset of  $\Delta_B$  and  $\Delta_B$  is a picture fuzzy soft subset of  $\delta_A$ . that is if  $(\delta, A) \subseteq (\Delta, B)$  and  $(\delta, B) \subseteq (\Delta, A)$  then  $\delta_A = \Delta_B$ .

### 3.6 Definition

Let  $\delta_A$  be a PFS set over  $U$ . The complement of  $\delta_A$ , denoted by  $\delta_A^C$ , where  $\delta_A^C : A \rightarrow PFS(U)$  is mapping given by  $\delta_{(e)}^C = \{\delta_{(e)}\}^C$  for all  $e \in A$ .

### 3.7 Example

Consider the PFS set  $\delta_A$  then the complement of  $\delta_A$  is represented as

$$(\delta_A)^C = \begin{matrix} & e_1 & e_2 & e_3 \\ \begin{matrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{matrix} & \left( \begin{array}{ccc} (0.1, 0.3, 0.6) & (0.2, 0.5, 0.3) & (0.4, 0.5, 0.7) \\ (0.6, 0.4, 0.9) & (0.5, 0.4, 0.3) & (0.9, 0.7, 0.1) \\ (0.9, 0.7, 0.3) & (0.7, 0.6, 0.4) & (0.7, 0.5, 0.2) \\ (0.8, 0.5, 0.2) & (0.9, 0.7, 0.5) & (0.7, 0.5, 0.3) \end{array} \right) \end{matrix}$$

By the suggestions given by Molodtsov, [14] we define the AND and OR operation on two PFS sets as follows.

### 3.8 Definition

Let  $\delta_A$  and  $\Delta_B$  are PFS sets over  $U$ . Then  $\delta_A$  AND  $\delta_B$ , denoted by  $\delta_A \cap \delta_B$ .



### 3.9 Example

Let  $U = \{C_1, C_2, C_3, C_4\}$  and  $E = \{e_1, e_2, e_3, e_4, e_5\}$ . Take  $A = \{e_1, e_2\}$  and  $B = \{e_1, e_3, e_5\}$ , define

$$\delta_A = \begin{matrix} & e_1 & e_2 \\ C_1 & (0.2, 0.3, 0.4) & (0.1, 0.3, 0.4) \\ C_2 & (0.1, 0.4, 0.6) & (0.3, 0.2, 0.1) \\ C_3 & (0.2, 0.0, 0.8) & (0.1, 0.3, 0.6) \\ C_4 & (0.1, 0.2, 0.4) & (0.2, 0.4, 0.1) \end{matrix} \text{ and}$$

$$\Delta_B = \begin{matrix} & e_1 & e_3 & e_5 \\ h_1 & (0.1, 0.7, 0.6) & (0.2, 0.4, 0.7) & (0.1, 0.3, 0.6) \\ h_2 & (0.2, 0.4, 0.3) & (0.1, 0.3, 0.8) & (0.2, 0.6, 0.7) \\ h_3 & (0.1, 0.3, 0.6) & (0.4, 0.6, 0.2) & (0.1, 0.4, 0.6) \\ h_4 & (0.7, 0.1, 0.8) & (0.7, 0.6, 0.3) & (0.1, 0.0, 0.2) \end{matrix}$$

Here  $\delta_A \cap \Delta_B = (H, C)$ , where  $C = A \cap B$  and  $\forall e \in C$

$$H(e) = \begin{cases} \delta(e), & \text{if } x e \in A - B \\ \Delta(e), & \text{if } x e \in B - A \\ \delta(e) \cap \Delta(e), & \text{if } e \in A \cap B \end{cases}$$

in this example

$$\delta_A \cap \Delta_B = (H, C) = \begin{matrix} & e_1 \\ h_1 & (0.2, 0.3, 0.4) \\ h_2 & (0.1, 0.4, 0.6) \\ h_3 & (0.2, 0.0, 0.8) \\ h_4 & (0.1, 0.2, 0.4) \end{matrix}$$

### 3.10 Definition

Let  $\delta_A$  and  $\Delta_B$  are PFS sets over  $U$ . Then  $\delta_A$  OR  $\Delta_B$ , denoted by  $\delta_A \cup \Delta_B$ .

$$\delta_A \cup \Delta_B = \begin{matrix} & (e_1, e_1) & (e_1, e_3) & (e_1, e_5) & (e_2, e_1) & (e_2, e_3) & (e_2, e_5) \\ C_1 & (0.2, 0.3, 0.4) & (0.2, 0.3, 0.7) & (0.1, 0.3, 0.6) & (0.1, 0.3, 0.6) & (0.1, 0.3, 0.7) & (0.1, 0.3, 0.6) \\ C_2 & (0.1, 0.4, 0.6) & (0.1, 0.3, 0.8) & (0.1, 0.4, 0.7) & (0.2, 0.2, 0.3) & (0.1, 0.2, 0.8) & (0.2, 0.2, 0.7) \\ C_3 & (0.1, 0.0, 0.8) & (0.2, 0.0, 0.8) & (0.1, 0.0, 0.8) & (0.1, 0.3, 0.6) & (0.1, 0.3, 0.6) & (0.1, 0.3, 0.6) \\ C_4 & (0.1, 0.1, 0.8) & (0.1, 0.2, 0.4) & (0.1, 0.0, 0.4) & (0.2, 0.1, 0.8) & (0.2, 0.4, 0.3) & (0.1, 0.0, 0.2) \end{matrix}$$

Here  $\delta_A \cup \Delta_B = (H, C)$ , where  $C = (A \cup B)$  and for all  $e \in C$ .

$$K(e) = \begin{cases} \delta(e), & \text{if } x e \in A - B \\ \Delta(e), & \text{if } x e \in B - A \\ \delta(e) \cup \Delta(e), & \text{if } e \in A \cap B \end{cases}$$

$$(\delta_A \cup \Delta_B) = (H, C) = \begin{matrix} & e_1 & e_2 & e_3 & e_5 \\ \begin{matrix} C_1 \\ C_2 \\ C_3 \\ C_4 \end{matrix} & \left( \begin{array}{cccc} (0.2, 0.3, 0.4) & (0.1, 0.3, 0.4) & (0.2, 0.4, 0.7) & (0.1, 0.3, 0.6) \\ (0.1, 0.4, 0.6) & (0.4, 0.2, 0.1) & (0.1, 0.3, 0.8) & (0.2, 0.6, 0.7) \\ (0.0, 0.0, 0.8) & (0.1, 0.3, 0.6) & (0.4, 0.3, 0.2) & (0.1, 0.4, 0.6) \\ (0.1, 0.2, 0.4) & (0.2, 0.4, 0.1) & (0.7, 0.6, 0.3) & (0.1, 0.0, 0.2) \end{array} \right) \end{matrix}$$

### 3.11 Theorem[Demorgon's Law]

Let  $\delta_A$  and  $\Delta_B$  be two PFS sets over  $U$ . Then (i)  $(\delta_A \cap \Delta_B)^C = \delta_A^C \cup \Delta_B^C$   
(ii)  $(\delta_A \cup \Delta_B)^C = \delta_A^C \cap \Delta_B^C$ .

Proof

$$\begin{aligned} (i) \text{ Suppose that } (\delta, A) \cap (\Delta, B) &= (K, A \times B) \\ (\delta, A) \cap (\Delta, B)^C &= (K, A \times B)^C \\ &= (K^C, A \times B) \\ \text{Now } (\delta, A)^C \cup (\Delta, B)^C &= (\delta^C, A) \cup (\Delta^C, B) \\ &= (H, A \times B). \end{aligned}$$

Take  $(\alpha, \beta) \in A \times B$ , Therefore

$$\begin{aligned} K^C(\alpha, \beta) &= \{K(\alpha, \beta)\}^C \\ &= \{\delta(\alpha) \cap \Delta(\beta)\}^C \\ &= \delta^C(\alpha) \cup \Delta^C(\beta) \\ \text{agian } H(\alpha, \beta) &= \delta^C(\alpha) \cup \Delta^C(\beta) \\ H^C(\alpha, \beta) &= H(\alpha, \beta) \end{aligned}$$

The theorem is proved

(ii) The result can be proved in a similar way.

### 3.12 Theorem

Union of two PFS sets  $\delta_A$  and  $\Delta_B$  is a PFS set.

Proof

We know that, Let  $(\delta_A)$  and  $(\Delta_B)$  are PFS sets over  $U$ . Then  $\delta_A$  OR  $\Delta_B$ , denoted by  $\delta_A \cup \Delta_B$ . and  $\forall e \in C, e \in A \rightarrow B$ , or  $e \in B \rightarrow A$ , then  $K(e) = \delta(e)$  or  $K(e) = \Delta(e)$ . So, in either case, we have  $K(e)$  is a picture fuzzy soft set. If  $e \in A \cap B$ , for a fixed  $x \in U$  without loss of generality, suppose  $\lambda_{\delta(e)}(x) \leq \lambda_{\Delta(e)}(x)$ ,

$$\begin{aligned} & \text{we have } \lambda_{K(e)}(x) + \mu_{K(e)}(x) + \gamma_{K(e)}(x) = \\ & \max\{\lambda_{\delta(e)}(x), \lambda_{\Delta(e)}(x)\} + \min\{\mu_{\delta(e)}(x), \mu_{\Delta(e)}(x)\} + \min\{\gamma_{\delta(e)}(x), \gamma_{\Delta(e)}(x)\} \\ & = \lambda_{\Delta(e)}(x) + \min\{\mu_{\delta(e)}(x), \mu_{\Delta(e)}(x)\} + \min\{\gamma_{\delta(e)}(x), \gamma_{\Delta(e)}(x)\} \\ & \leq \lambda_{\Delta(e)}(x) + \mu_{\Delta(e)}(x) + \gamma_{\Delta(e)}(x) \leq 1 \end{aligned}$$

Therefore  $(K, C)$  is a PFS set.

Hence the proof.

### 3.13 Theorem

Intersection of two PFS sets  $\delta_A$  and  $\Delta_B$  is a PFS set.

Proof

we know that, Let  $\delta_A$  and  $\Delta_B$  are PFS sets over  $U$ . Then  $\delta_A$  OR  $\Delta_B$ , denoted by  $\delta_A \cap \Delta_B$ . and  $\forall e \in U$ , without loss of generality suppose  $\lambda_{\delta(e)}(x) \leq \lambda_{\Delta(e)}(x)$ ,

$$\begin{aligned} & \text{we have } \lambda_{K(e)}(x) + \mu_{K(e)}(x) + \gamma_{K(e)}(x) = \\ & \min\{\lambda_{\delta(e)}(x); \lambda_{\Delta(e)}(x)\} + \max\{\mu_{\delta(e)}(x), \mu_{\Delta(e)}(x)\} + \max\{\gamma_{\delta(e)}(x), \gamma_{\Delta(e)}(x)\} \\ & = \lambda_{\Delta(e)}(x) + \min\{\mu_{\delta(e)}(x), \mu_{\Delta(e)}(x)\} + \max\{\gamma_{\delta(e)}(x), \gamma_{\Delta(e)}(x)\} \\ & \leq \lambda_{\Delta(e)}(x) + \mu_{\Delta(e)}(x) + \gamma_{\Delta(e)}(x) \leq 1 \end{aligned}$$

Therefore  $(K, C)$  is a PFS set. Hence the proof.

### 3.14 Theorem

Let  $\delta_A, \Delta_B$  and  $K_C$  be PFS sets over  $U$ . Then (i)  $\delta_A \cap \delta_B = \delta_A$  (ii)  $\delta_A \cup \delta_A = \delta_A$ .

(iii)  $(\delta_A \cap \Delta_B) = (\Delta_B \cup \delta_A)$  (iv)  $(\delta_A \cup \Delta_B) = (\Delta_B \cap \delta_A)$ .

(v)  $(\delta_A \cup \Delta_B) \cup K_C = \delta \cup (\Delta_B \cup K_C)$  (vi)  $(\delta_A \cap \Delta_B) \cap K_C = \delta \cap (\Delta_B \cap K_C)$ .

Proof

The proofs are straightforward by using the definitions((3.5),(3.8),(3.10)) and Theorem(3.11)

(i) Let  $\delta_A$  and  $\Delta_B$  are PFS sets over  $U$ . Then  $\delta_A$  AND  $\delta_B$ , denoted by  $\delta_A \cap \delta_B$ .

(ii) Let  $\delta_A$  and  $\Delta_B$  are PFS sets over  $U$ . Then  $\delta_A$  OR  $\delta_B$ , denoted by  $\delta_A \cup \delta_B$

(iii) Let  $A, B, C \in PF(R)$ , then (i) If  $A \subseteq B$  and  $B \subseteq C$  then  $A \subseteq C$

(ii)  $(A^C)^C = A$

(iii) Operations  $\cap$  and  $\cup$  are commutative, associative and distributive.

### 3.15 Theorem[Distributive Law]

Let  $\delta_A, \Delta_B$  and  $K_C$  be PFS sets over  $U$ . Then (i)  $\delta_A \cap (\Delta_B \cup K_C) = (\delta_A \cap \Delta_B) \cup (\delta_A \cap K_C)$  (ii)  $\delta_A \cup (\Delta_B \cap K_C) = (\delta_A \cup \Delta_B) \cap (\delta_A \cup K_C)$

Proof

The proofs are straightforward by using the definition((3.5),(3.8),(3.10)) and Theorem(3.14).

(i) Let  $\delta_A$  and  $\Delta_B$  are PFS sets over  $U$ . Then  $\delta_A$  AND  $\delta_B$ , denoted by " $\delta_A \cap \delta_B$ ".

(ii) Let  $\delta_A$  and  $\Delta_B$  are PFS sets over  $U$ . Then  $\delta_A$  OR  $\delta_B$ , denoted by " $\delta_A \cup \delta_B$ ".

(iii) Let  $A, B, C \in PF(R)$ , then (iv) If  $A \subseteq B$  and  $B \subseteq C$  then  $A \subseteq C$

(v)  $(A^C)^C = A$

(iii) Operations  $\cap$  and  $\cup$  are commutative, associative and distributive.

### 3.16 Theorem[Dual Law]

Let  $\delta_A, \Delta_B$  and  $K_C$  be PFS sets over  $U$ . Then (i)  $(\delta_A \cap \Delta_B)^C = \delta_A^C \cup \Delta_B^C$ , if and only if  $A=B$

(ii)  $(\delta_A \cup \Delta_B)^C = \delta_A^C \cap \Delta_B^C$ . iff  $A=B$

Proof

(i) If  $A=B$ , Then we have  $\delta_A \cup \Delta_B = \delta_A \cup \Delta_A = (K, A)$ . Now for all  $e \in A$ ,  $K(e) = \delta(e) \cup \Delta(e)$  Hence  $(\delta_A \cap \Delta_B)^C = (\delta_A \cap \Delta_A)^C = (K, A)^C = (K^C, A)$  and  $K^C(e) = (\delta(e) \cup \Delta(e))^C = \delta^C(e) \cap \Delta^C(e)$  Again suppose that  $(\delta_A \cap \Delta_B)^C = (\delta_A \cap \Delta_A)^C = (I, A)^C = (I^C, A) = (I, A)$  for all  $e \in A$ .  $I(e) = \delta^C(e) \cup \Delta^C(e)$  we see that for all  $e \in A$ .  $I(e) = K^C(e)$ . therefore this result is true.

Conversely ,hypotheses  $A \neq B$ . Suppose that  $\delta_A \cup \Delta_B = (K, C)$  where  $C = A \cup B$  and for all  $e \in C$ .

$$K(e) = \begin{cases} \delta(e), & \text{if } x e \in A - B \\ \Delta(e), & \text{if } x e \in B - A \\ \delta(e) \cup \Delta(e), & \text{if } e \in A \cap B \end{cases}$$

Thus  $(\delta_A \cup \Delta_B)^C = K_C^C$  and

$$K^C(e) = \begin{cases} \delta^C(e), & \text{if } x e \in A - B \\ \Delta^C(e), & \text{if } x e \in B - A \\ \delta^C(e) \cap \Delta^C(e), & \text{if } e \in A \cap B \end{cases}$$

Again suppose that  $\delta_A^C \cap \Delta_B^C = (I, J)$ . Where  $J = A \cap B$  and  $\forall e \in J$ .  $I(e) = \delta^C(e) \cap \Delta^C(e)$ . obviously, where  $A \neq B$ , we have  $C = A \cup B \neq A \cap B = J$ , so  $K_C^C \neq I_J$ . This is contradiction of over condition.  $(\delta_A \cap \Delta_B)^C = \delta_A^C \cup \Delta_B^C$ . Hence  $A=B$ .

(ii) This result can be proved in a similar way.

### 3.17 Remark

From the above theorem for dual theorem ,we know that Demorgon's laws are invalied for PFS sets with the different parameters sets, but they are true for PFS sets with the identical parameter set.

## 4 Picture Fuzzy Soft Relations and its Decision Making

In this section ,we construct picture fuzzy soft operator and a decision making method on relations.

Now we construct a decision making method on picture fuzzy soft relation by the following algorithm:

**step-1** Input the picture fuzzy soft sets  $A$  and  $B$

**step-2** Obtain the picture fuzzy soft matrix  $R$  corresponding to contesection product of  $A$  and  $B$  respectively.

**step-3** Compute the comparision table using the following formula  $P_A(r) + I_A(r) - N_A(r)$ .

**step-4** Select the high numerical grades from comparison table for each row.

**step-5** Find the solve table which having the following form

$R$	$(x_1, y_1)$	...	...	$(x_n, y_n)$
<i>(Objects)</i>	$h_1$			
<i>(Highestgrade)</i>				

where  $X_n$  denotes the parameter of  $A$  and  $y_n$  denotes the parameter of  $B$ .

**step-6** Compute the solve of each objects by taking the sum of these numerical grades.

**step-7** Find  $m$ , for which  $S_m = \max S_j$ . then  $S_m$  is the high score, if  $m$  has most then one values, you can choose any one value  $S_j$ .

Now we use this algorithm to find the best choice in decision making system.

### 4.1 Example

Let  $U = \{u_1, u_2, u_3, u_4\}$  be the set of four cars. suppose that two friends want to buy a car for a mutual friend among these four cars according to their choice parameters  $E_1 = \{x_1, x_2, x_3\} = \{\text{Expensive, moderate, inexpensive}\}$  and  $E_2 = \{y_1, y_2, y_3\} = \{\text{Green, Black, Red}\}$  respectively, then we select a car on the basis of the sets of friends parameters by using the picture fuzzy soft relation decision making method.

**step-1** We input the picture fuzzy soft set  $A$  and  $B$  as

$$A = \begin{matrix} & \begin{matrix} u_1 & u_2 & u_3 & u_4 \end{matrix} \\ \begin{matrix} x_1 \\ x_2 \\ x_3 \end{matrix} & \begin{pmatrix} (0.3, 0.6, 0.4) & (0.2, 0.4, 0.5) & (0.3, 0.6, 0.7) & (0.3, 0.5, 0.7) \\ (0.1, 0.3, 0.4) & (0.1, 0.3, 0.3) & (0.2, 0.4, 0.5) & (0.1, 0.3, 0.9) \\ (0.3, 0.3, 0.4) & (0.4, 0.6, 0.7) & (0.3, 0.4, 0.5) & (0.3, 0.7, 0.9) \end{pmatrix} \end{matrix}$$

$$\text{and } B = \begin{matrix} & \begin{matrix} u_1 & u_2 & u_3 & u_4 \end{matrix} \\ \begin{matrix} x_1 \\ x_2 \\ x_3 \end{matrix} & \begin{pmatrix} (0.4, 0.6, 0.7) & (0.2, 0.4, 0.5) & (0.4, 0.4, 0.6) & (0.3, 0.5, 0.9) \\ (0.2, 0.3, 0.5) & (0.3, 0.5, 0.6) & (0.2, 0.4, 0.5) & (0.1, 0.5, 0.9) \\ (0.2, 0.3, 0.4) & (0.2, 0.8, 0.8) & (0.3, 0.6, 0.6) & (0.1, 0.4, 0.7) \end{pmatrix} \end{matrix}$$

**step-2** we obtain the picture fuzzy soft matrix  $R$  corresponding to cartesian product of  $A$  and  $B$  respectively

$R$	$u_1$	$u_2$	$u_3$	$u_4$
$(x_1, y_1)$	(0.3, 0.6, 0.7)	(0.2, 0.4, 0.5)	(0.3, 0.5, 0.7)	(0.3, 0.5, 0.7)
$(x_1, y_2)$	(0.1, 0.45, 0.4)	(0.2, 0.45, 0.6)	(0.2, 0.5, 0.7)	(0.1, 0.45, 0.9)
$(x_1, y_3)$	(0.2, 0.45, 0.7)	(0.2, 0.6, 0.8)	(0.3, 0.6, 0.7)	(0.1, 0.45, 0.7)
$(x_2, y_1)$	(0.1, 0.45, 0.7)	(0.1, 0.4, 0.6)	(0.2, 0.4, 0.6)	(0.1, 0.4, 0.9)
$(x_2, y_2)$	(0.1, 0.3, 0.5)	(0.1, 0.4, 0.6)	(0.2, 0.4, 0.5)	(0.1, 0.4, 0.9)
$(x_2, y_3)$	(0.1, 0.3, 0.4)	(0.1, 0.055, 0.8)	(0.2, 0.5, 0.6)	(0.1, 0.35, 0.9)
$(x_3, y_1)$	(0.3, 0.4, 0.7)	(0.2, 0.5, 0.7)	(0.3, 0.4, 0.6)	(0.3, 0.06, 0.9)
$(x_3, y_2)$	(0.2, 0.3, 0.5)	(0.3, 0.055, 0.7)	(0.2, 0.4, 0.5)	(0.3, 0.6, 0.7)
$(x_3, y_3)$	(0.2, 0.3, 0.4)	(0.2, 0.7, 0.8)	(0.3, 0.5, 0.6)	(0.3, 0.6, 0.9)

Table -2 picture fuzzy soft relational matrix  $R$ .

**Step-3** By using table-1, we compute the comparison table as

$R$	$u_1$	$u_2$	$u_3$	$u_4$
$(x_1, y_1)$	0.2	0.1	0.1	0.1
$(x_1, y_2)$	-0.15	0.05	0	-0.35
$(x_1, y_3)$	-0.05	0.00	0.2	-0.15
$(x_2, y_1)$	-0.15	-0.1	0.00	-0.4
$(x_2, y_2)$	-0.1	-0.1	0.1	-0.4
$(x_2, y_3)$	0.00	-0.645	0.1	-0.45
$(x_3, y_1)$	0.05	0.00	0.1	-0.54
$(x_3, y_2)$	0.00	-0.345	0.1	0.2
$(x_3, y_3)$	0.1	0.1	0.2	0.2

Table -2 comparison table (P+I-N).

**step-4** we select the highest numerical numerical grade from step-3 for each row

$R$	$u_1$	$u_2$	$u_3$	$u_4$
$(x_1, y_1)$	0.2	0.1	0.1	0.1
$(x_1, y_2)$	-0.15	0.05	0	-0.35
$(x_1, y_3)$	-0.05	0.00	0.2	-0.15
$(x_2, y_1)$	-0.15	-0.1	0.00	-0.4
$(x_2, y_2)$	-0.1	-0.1	0.1	-0.4
$(x_2, y_3)$	0.00	-0.645	0.1	-0.45
$(x_3, y_1)$	0.05	0.00	0.1	-0.54
$(x_3, y_2)$	0.00	-0.345	0.1	0.2
$(x_3, y_3)$	0.1	0.1	0.2	-0.745

Table-3 Highest value of each row

**step-5** we find the score table which have the following form

$R$	$u_1$	$u_2$	$u_3$	$u_4$
$(x_1, y_1)$	0.2	—	—	—
$(x_1, y_2)$	—	0.05	—	—
$(x_1, y_3)$	—	—	0.2	—
$(x_2, y_1)$	—	—	0	—
$(x_2, y_2)$	—	—	0.1	—
$(x_2, y_3)$	—	—	0.1	—
$(x_3, y_1)$	—	—	0.1	—
$(x_3, y_2)$	—	—	—	0.2
$(x_3, y_3)$	—	—	0.2	—

.

Table -4 is score table.

**step-6** we compute the score of each objects by taking the form of numerical grades as;

$$u_1 = 0.2,$$

$$u_2 = 0.05,$$

$$u_3 = 0.2 + 0 + 0.1 + 0.1 + 0.2 = 0.7,$$

$$u_4 = 0.2$$

**step-7** The maximum value of the score value is  $S_j = 0.7$ ,so the two friends will select the car with the highest score ,hence they will choose car  $u_3$ . with parameter either expensive carwith red or expensive with red.

## 5 Conclusion

We have defined a picture fuzzy soft set with some special operations and proved various result based on the picture fuzzy soft set.Finally we study the decision making approach for solving picture fuzzy soft matrix under relational concepts.one can obtian the similar result in fermatean fuzzy soft set and pythogoner fuzzy soft sets.



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