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Approximations of Fuzzy PredicatesThrough Rough Computing

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Abstract-As Fuzzy Predicates have enormous applications in Artificial Intelligence and Machine Learning, the authors focus on deriving a Mathematical Tool for approximating Fuzzy Predicates through Rough Sets. In this paper, we discuss the modified implication, Equivalence rules and Normal forms of Fuzzy Predicates through Rough Computing.

Index Terms- Logic, Fuzzy Logic, Fuzzy Predicates, Rough Sets, Machine Learning, Implication Rules, Normal Forms

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1. INTRODUCTION

The theory of Fuzziness, invented in 1965 by L.Zadeh, finds various real time applications where the conventional tools lack with accuracy. In recent days, several fuzzy systems are in use which involve fuzzy predicates. Considering the importance, G.Ganesanet.al, [4] have demonstrated the basic definitions on Fuzzy Predicates through Rough Sets. Later, G.Ganesan et.al, made various contributions on deriving implication and equivalence rules along with the normal forms. In this paper, we summarize the contributions made by them.

This paper is organized into Fivesections. Second section deals with the Mathematical Preliminaries; Third section deals with the concepts such as Implication rules and Equivalence Rules in Fuzzy Predicates under Rough Approximations; Fourth section deals with the Normal Forms and the paper is concluded with the concluding remarks as Fifth section.

2. MATHEMATICAL PRELIMARIES

In this section, we discuss the mathematical concepts related to this paper.

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2.1 Rough Sets

For a given equivalence relation R on the universe of discourse U, we define $\underline{R}X=\cup\{Y\in U/R: Y\subseteq X\}$ and $\overline{R}X=\cup\{Y\in U/R: Y\cap X\neq\Phi\}$ where U/R denote the quotient space and$\underline{R}X$ and $\overline{R}X$ are said to be R-lower and R-upper approximations of X and $(\underline{R}X, \overline{R}X)$ is called *R-rough set*. If X is R-definable then $\underline{R}X=\overline{R}X$ otherwise X is R-Rough [1,10]. The boundary $BN_R(X)$ is defined as $BN_R(X)=\overline{R}X-\underline{R}X$. Hence, if X is R-definable, then $BN_R(X)=\Phi$. Any object in $\underline{R}X$ gives the certainty of the object in X with respect to R. Any object in $\overline{R}X$ gives the possibility of the object in X with respect to R. Hence, $\underline{R}X$ is called R-positive region of X and $U-\overline{R}X$ is called the R-negative region of X.

2.2 Fuzzy Sets

Fuzzy sets [5] are obtained by replacing the co-domain of the characteristic function of classical set theory into [0,1]. Here, the function defined is called as membership function and the value assumed by the membership function is called the grade of membership in the given fuzzy set. In precise, for the given universe of discourse $U=\{x_1,x_2,\ldots,x_n\}$, any fuzzy subset A is defined as $\left\{\frac{\mu_A(x_1)}{x_1}+\frac{\mu_A(x_2)}{x_2}+\ldots.+\frac{\mu_A(x_n)}{x_n}\right\}$ where μ_A is the membership function defined from U to [0,1]. However, for convention, we denote $A = (\mu_A(x_1), \mu_A(x_2),\ldots.,\mu_A(x_n))$. For a given $\alpha\in(0,1)$, the strong α-cut of a fuzzy set A is defined as $\{x\in U: \mu_A(x)>\alpha\}$ and is denoted by $A[\alpha]$.For any two fuzzy sets A and B, their union and intersection of the membership values of each x_i is obtained as $\mu_{A\cup B}(x_i)=\max(\mu_A(x_i), \mu_B(x_i))$ and $\mu_{A\cap B}(x_i)=\min(\mu_A(x_i), \mu_B(x_i))$ respectively. For any fuzzy set A, the complement of of each x_i is given by $\mu_{A^c}(x_i) =1-\mu_A(x_i)\ \forall\ x_i\in U$.

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2.3. Analysis of fuzzy set using a threshold

Firstly, we construct a set D, called **R-domain**[2] satisfying the following properties:

a) $D \subset (0,1)$
b) If a fuzzy set A is under computation, eliminate the values $\mu_A(x)$ and $\mu_{A^c}(x)$ $\forall x \in U$ from the domain D, if they exist.
c) After the computation using A, the values removed in (b) may be included in D provided A must not involve in further computation

Consider the universe of discourse $U=\{x_1,x_2,\ldots,x_n\}$. Let $\alpha,\alpha_1,\alpha_2,\beta$ be the thresholds assume one of the values from the domain D, where D is constructed using the fuzzy sets A and B. Then the following properties can be obtained.

- $A[\alpha_1] \cup A[\alpha_2]=A[\alpha]$ where $\alpha=\min(\alpha_1,\alpha_2)$
- $A[\alpha_1] \cap A[\alpha_2]=A[\alpha]$ where $\alpha=\max(\alpha_1,\alpha_2)$
- $(A \cup B)[\alpha]=A[\alpha] \cup B[\alpha]$
- $(A \cap B)[\alpha]=A[\alpha] \cap B[\alpha]$
- $A^c[\alpha]=A[1-\alpha]^c$
- $(A \cup B)^c[\alpha]=A^c[\alpha] \cap B^c[\alpha]$
- $(A \cap B)^c[\alpha]=A^c[\alpha] \cup B^c[\alpha]$

2.4. Rough set approach on fuzzy sets

Let Ψ be any partition of U, say $\{B_1,B_2,\ldots,B_t\}$. For the given fuzzy set A, the lower and upper approximations with respect to α can be defined as $A_\alpha=\underline{(A[\alpha])}$ and $A^\alpha=\overline{(A[\alpha])}$ respectively. Here, by using the properties of rough sets, the following properties can be obtained.

- $(A \cup B)^\alpha=A^\alpha \cup B^\alpha$
- $(A \cap B)_\alpha=A_\alpha \cap B_\alpha$
- $(A \cup B)_\alpha \supseteq A_\alpha \cup B_\alpha$
- $(A \cap B)^\alpha \subseteq A^\alpha \cap B^\alpha$
- $(A^c)^\alpha=(A_{1-\alpha})^c$
- $(A^c)_\alpha=(A^{1-\alpha})^c$

2.5 Fuzzy Logic

In Boolean logic, a logical proposition is assigned to a crisp set in the universe of discourse. The variables such as 'beautiful, 'brilliant' etc., cannot be used in Boolean logic. These variables 'values are words in a natural language. Such variables are called as the linguistic variables. The linguistic variables take the grade of membership ranging from 0 to 1. Linguistic variables collect elements into similar groups where we can deal with less precisely and hence we can handle more complex systems. The logic developed for processing such linguistic variables is called fuzzy logic. As the paper is confined with the fuzzy predicates, we directly provide the connectives on fuzzy predicates.

For any two fuzzy predicates P(a) and Q(b),

- conjunction ($\wedge$) is defined by $\mu_{(P(a) \wedge Q(b))} = \min(\mu_{P(a)}, \mu_{Q(b)})$
- disjunction ($\wedge$) is defined by $\mu_{(P(a) \vee Q(b))} = \max(\mu_{P(a)}, \mu_{Q(b)})$
- negation (neg) is defined by $\mu_{(neg(P(a)))} = 1 - \mu_{P(a)}$
- implication P(a) $\to$ Q(b) is defined by $\mu_{(P(a) \to Q(b))} = \max(1-\mu_{P(a)}, \mu_{Q(b)})$
- bi-implication P(a) $\leftrightarrow$ Q(b) is defined by $\mu_{(P(a) \leftrightarrow Q(b))} = \min(\mu_{P(a) \to Q(b)}, \mu_{Q(b) \to P(a)})$

3. FUZZY PREDICATES THROUGH ROUGH APPROXIMATIONS

For the given fuzzy predicate P, denote P{x} as the grade of membership of P(x). Then, the negation of P(x) is given by its membership function 1-P{x} and is denoted by 'neg P(x)'.Consider the collection of fuzzy predicates $\{P_1,P_2,\ldots,P_k\}$ and the arguments $\{x_1,x_2,\ldots,x_n\}$. Let X be any partition defined on the collection on the collection of all arguments using some equivalence relation. Then P_i can be denoted as $P_i=(P_i\{x_1\}, P_i\{x_2\},\ldots, P_i\{x_n\})$. The complement of P_i is given by $P_i^c=(1-P_i\{x_1\}, 1-P_i\{x_2\},\ldots, 1-P_i\{x_n\})$. From this, it can be observed that the grades of membership of the elements of P_i^c are merely the grades of membership of the negations of $P_i(x)$.Define the set $M=\{s/s=P_i\{x_j\}$ or $s=1-P_i\{x_j\};$ $i=1,2,\ldots,k;$ $j=1,2,\ldots,n\}$. Let $\alpha \in (0,1)-M$. For each α, define $P[\alpha]=\{x: P\{x\}>\alpha\}$.The lower and upper rough approximations are defined by $P_\alpha=\underline{P[\alpha]}$ and $P^\alpha=\overline{P[\alpha]}$ respectively.If $x \in P_\alpha$ then define $P_\alpha(x)$ is true otherwise it is false. If $x \in P^\alpha$, then define $P^\alpha(x)$ is true otherwise it is false. As $P_\alpha \subseteq P^\alpha$, if $P_\alpha(x)$ is true then $P^\alpha(x)$ is true. Thus, for each fuzzy predicate P, the lower and upper predicates, which are crisp, can be defined with respect to α. Also, it may be verified that $(negP_i(x))_\alpha = \tau(P_i^{1-\alpha}(x))$ and $(negP_i(x))^\alpha = \tau(P_{i,1-\alpha}(x))$ where τ represents negation in usual predicate calculus.

3.1 Rough Connectives

In this section, the connectives are introduced similar to the connectives used in the predicate calculus.For the given fuzzy predicates $P_i(x)$ and $P_j(y)$,

- **Rough conjunction:** lower and upper conjunctions $\underset{\alpha}{\wedge}$ and $\overset{\alpha}{\wedge}$ are defined as $P_i(x) \underset{\alpha}{\wedge} P_j(y) = P_{i,\alpha}(x) \wedge P_{j,\alpha}(y)$ and $P_i(x) \overset{\alpha}{\wedge} P_j(y) = P_i^{\alpha}(x) \wedge P_j^{\alpha}(y)$ respectively.
- **Rough disjunction:** lower and upper disjunctions $\underset{\alpha}{\vee}$ and $\overset{\alpha}{\vee}$ are defined as $P_i(x) \underset{\alpha}{\vee} P_j(y) = P_{i,\alpha}(x) \vee P_{j,\alpha}(y)$ and $P_i(x) \overset{\alpha}{\vee} P_j(y) = P_i^{\alpha}(x) \vee P_j^{\alpha}(y)$ respectively.
- **Rough implication:** lower and upper implications $\xrightarrow[\alpha]{}$ and $\xrightarrow{\alpha}$ are defined as $P_i(x) \xrightarrow[\alpha]{} P_j(y) = P_i^{1-\alpha}(x) \rightarrow P_{j,\alpha}(y)$ and $P_i(x) \xrightarrow{\alpha} P_j(y) = P_{i,1-\alpha}(x) \rightarrow P_j^{\alpha}(y)$ respectively.
- **Rough bi-implication:** lower and upper bi-implications $\xleftrightarrow[\alpha]{}$ and $\xleftrightarrow{\alpha}$ are defined as $P_i(x) \xleftrightarrow[\alpha]{} P_j(y) = [P_i(x) \xrightarrow[\alpha]{} P_j(y)] \wedge [P_j(y) \xrightarrow[\alpha]{} P_i(x)]$ and $P_i(x) \xleftrightarrow{\alpha} P_j(y) = [P_i(x) \xrightarrow{\alpha} P_j(y)] \wedge [P_j(y) \xrightarrow{\alpha} P_i(x)]$ respectively.
- **Rough negation:** lower and upper negations τ_α and τ^α are defined as $\tau_\alpha P_i(x) = (negP_i(x))_\alpha = \tau(P_i^{1-\alpha}(x))$ and $\tau^\alpha P_i(x) = (negP_i(x))^\alpha = \tau(P_{i,1-\alpha}(x))$ respectively

The detailed study on these connectives are made in [3,7,8,9]. Now, we provide the implication and Equivalence rules on Fuzzy Predicates through the above definitions.

3.1.1 Implication Rules

G.Ganesanet.al., have described the implication rules on approximations on fuzzy predicates. The Implication Rules are given below:

	Lower Implications
LI1	$\dfrac{(P(x) \underset{\alpha}{\wedge} Q(y))}{\therefore P_\alpha(x)}$
LI2	$\dfrac{(P(x) \underset{\alpha}{\wedge} Q(y))}{\therefore Q_\alpha(y)}$
LI3	$\dfrac{P_\alpha(x)}{\therefore (P(x) \underset{\alpha}{\vee} Q(y))}$
LI4	$\dfrac{Q_\alpha(y)}{\therefore (P(x) \underset{\alpha}{\vee} Q(y))}$
LI5	$\dfrac{\tau(P_\alpha(x))}{\therefore P(x) \xrightarrow[\alpha]{} Q(y)}$
LI6	$\dfrac{Q_\alpha(y)}{\therefore P(x) \xrightarrow[\alpha]{} Q(y)}$
LI7	$\dfrac{\tau(P(x) \xrightarrow[\alpha]{} Q(y))}{\therefore P_\alpha(x)}$
LI8	$\dfrac{\tau(P(x) \xrightarrow[\alpha]{} Q(y))}{\therefore \tau(Q_\alpha(y))}$
LI9	$\dfrac{\begin{array}{l}(P_\alpha(x) \vee Q_\alpha(y))\\ \tau(P_\alpha(x))\end{array}}{\therefore Q_\alpha(y)}$
LI10	$\dfrac{\begin{array}{l}P_\alpha(x)\\ (P(x) \xrightarrow[\alpha]{} Q(y))\end{array}}{\therefore Q_\alpha(y)}$
LI11	$\dfrac{\begin{array}{l}(neg(Q(y))_\alpha\\ (P(x) \xrightarrow[\alpha]{} Q(y))\end{array}}{\therefore (neg(P(x))_\alpha}$
LI12	$\dfrac{\begin{array}{l}\tau(Q_\alpha(y))\\ (P(x) \xrightarrow[\alpha]{} Q(y))\end{array}}{\therefore \tau(P_\alpha(x))}$
LI13	$\dfrac{\begin{array}{l}(P(x) \xrightarrow[\alpha]{} Q(y))\\ (Q(y) \xrightarrow[\alpha]{} R(z))\end{array}}{\therefore (P(x) \xrightarrow[\alpha]{} R(z))}$
LI14	$\dfrac{\begin{array}{l}(P(x) \underset{\alpha}{\vee} Q(y))\\ (P(x) \xrightarrow[\alpha]{} R(z))\\ (Q(y) \xrightarrow[\alpha]{} R(z))\end{array}}{\therefore R_\alpha(z)}$
	Upper Implications
UI1	$\dfrac{(P(x) \overset{\alpha}{\wedge} Q(y))}{\therefore P^\alpha(x)}$
UI2	$\dfrac{(P(x) \overset{\alpha}{\wedge} Q(y))}{\therefore Q^\alpha(y)}$
UI3	$\dfrac{P^\alpha(x)}{\therefore (P(x) \overset{\alpha}{\vee} Q(y))}$
UI4	$\dfrac{Q^\alpha(y)}{\therefore (P(x) \overset{\alpha}{\vee} Q(y))}$

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UI5	$\dfrac{\tau(P^{\alpha}(x))}{\therefore P(x)\xrightarrow{\alpha}Q(y)}$
UI6	$\dfrac{Q^{\alpha}(y)}{\therefore P(x)\xrightarrow{\alpha}Q(y)}$
UI7	$\dfrac{\tau(P(x)\xrightarrow{\alpha}Q(y))}{\therefore P^{\alpha}(x)}$
UI8	$\dfrac{\tau(P(x)\xrightarrow{\alpha}Q(y))}{\therefore \tau(Q^{\alpha}(y))}$
UI9	$\begin{array}{l}(P^{\alpha}(x)\vee Q^{\alpha}(y))\\ \tau(P^{\alpha}(x))\\ \hline \therefore Q^{\alpha}(y)\end{array}$
UI10	$\begin{array}{l}P^{\alpha}(x)\\ (P(x)\xrightarrow{\alpha}Q(y))\\ \hline \therefore Q^{\alpha}(y)\end{array}$
UI11	$\begin{array}{l}(neg(Q(y))^{\alpha}\\ (P(x)\xrightarrow{\alpha}Q(y))\\ \hline \therefore (neg(P(x))^{\alpha}\end{array}$
UI12	$\begin{array}{l}\tau(Q^{\alpha}(y))\\ (P(x)\xrightarrow{\alpha}Q(y))\\ \hline \therefore \tau(P^{\alpha}(x))\end{array}$
UI13	$\begin{array}{l}(P(x)\xrightarrow{\alpha}Q(y))\\ (Q(y)\xrightarrow{\alpha}R(z))\\ \hline \therefore (P(x)\xrightarrow{\alpha}R(z))\end{array}$
UI14	$\begin{array}{l}(P(x)\overset{\alpha}{\vee}Q(y))\\ (P(x)\xrightarrow{\alpha}R(z))\\ (Q(y)\xrightarrow{\alpha}R(z))\\ \hline \therefore R^{\alpha}(z)\end{array}$

3.1.2 Equivalence Rules

G.Ganesanet.al, have described the equivalence rules on approximations on fuzzy predicates. The Equivalence Rules are given below:

LE$_1$	$\tau(\tau(P_{\alpha}(x))) = P_{\alpha}(x)$
UE$_1$	$\tau(\tau(P^{\alpha}(x))) = P^{\alpha}(x)$
LE$_2$	$(P(x)\underset{\alpha}{\wedge}P(x)) = P_{\alpha}(x)$
UE$_2$	$(P(x)\overset{\alpha}{\wedge}P(x)) = P^{\alpha}(x)$
LE$_3$	$(P(x)\underset{\alpha}{\vee}P(x)) = P_{\alpha}(x)$
UE$_3$	$(P(x)\overset{\alpha}{\vee}P(x)) = P^{\alpha}(x)$
LE$_4$	$P(x)\underset{\alpha}{\wedge}Q(y) = Q(y)\underset{\alpha}{\wedge}P(x)$
UE$_4$	$P(x)\overset{\alpha}{\wedge}Q(y) = Q(y)\overset{\alpha}{\wedge}P(x)$
LE$_5$	$P(x)\underset{\alpha}{\vee}Q(y) = Q(y)\underset{\alpha}{\vee}P(x)$
UE$_5$	$P(x)\overset{\alpha}{\vee}Q(y) = Q(y)\overset{\alpha}{\vee}P(x)$
LE$_6$	$(P(x)\underset{\alpha}{\wedge}Q(y))\underset{\alpha}{\wedge}R(z) =$ $P(x)\underset{\alpha}{\wedge}(Q(y)\underset{\alpha}{\wedge}R(z))$
UE$_6$	$(P(x)\overset{\alpha}{\wedge}Q(y))\overset{\alpha}{\wedge}R(z) =$ $P(x)\overset{\alpha}{\wedge}(Q(y)\overset{\alpha}{\wedge}R(z))$
LE$_7$	$(P(x)\underset{\alpha}{\vee}Q(y))\underset{\alpha}{\vee}R(z) =$ $P(x)\underset{\alpha}{\vee}(Q(y)\underset{\alpha}{\vee}R(z))$
UE$_7$	$(P(x)\overset{\alpha}{\vee}Q(y))\overset{\alpha}{\vee}R(z) =$ $P(x)\overset{\alpha}{\vee}(Q(y)\overset{\alpha}{\vee}R(z))$
LE$_8$	$P(x)\underset{\alpha}{\wedge}(Q(y)\underset{\alpha}{\vee}R(z)) =$ $(P(x)\underset{\alpha}{\wedge}Q(y))\underset{\alpha}{\vee}(P(x)\underset{\alpha}{\wedge}R(z))$
UE$_8$	$P(x)\overset{\alpha}{\wedge}(Q(y)\overset{\alpha}{\vee}R(z)) =$ $(P(x)\overset{\alpha}{\wedge}Q(y))\overset{\alpha}{\vee}(P(x)\overset{\alpha}{\wedge}R(z))$
LE$_9$	$P(x)\underset{\alpha}{\vee}(Q(y)\underset{\alpha}{\wedge}R(z)) =$ $(P(x)\underset{\alpha}{\vee}Q(y))\underset{\alpha}{\wedge}(P(x)\underset{\alpha}{\vee}R(z))$
UE$_9$	$P(x)\overset{\alpha}{\vee}(Q(y)\overset{\alpha}{\wedge}R(z)) =$ $(P(x)\overset{\alpha}{\vee}Q(y))\overset{\alpha}{\wedge}(P(x)\overset{\alpha}{\vee}R(z))$
LE$_{10}$	$P(x)\underset{\alpha}{\wedge}(negP(x)) = .f.$
UE$_{10}$	$P(x)\overset{\alpha}{\wedge}(negP(x)) = .f.$
LE$_{11}$	$P(x)\underset{\alpha}{\vee}(negP(x)) = .t.$
UE$_{11}$	$P(x)\overset{\alpha}{\vee}(negP(x)) = .t.$
LE$_{12}$	$P(x)\underset{\alpha}{\wedge}.f. = .f.$
UE$_{12}$	$P(x)\overset{\alpha}{\wedge}.f. = .f.$
LE$_{13}$	$P(x)\underset{\alpha}{\vee}.t. = .t.$
UE$_{13}$	$P(x)\overset{\alpha}{\vee}.t. = .t.$
LE$_{14}$	$P(x)\underset{\alpha}{\wedge}.t. = P_{\alpha}(x)$
UE$_{14}$	$P(x)\overset{\alpha}{\wedge}.t. = P^{\alpha}(x)$

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LE15	$P(x)\underset{\alpha}{\vee}.f. = P_{\alpha}(x)$
UE15	$P(x)\overset{\alpha}{\vee}.f. = P^{\alpha}(x)$
LE16	$P(x)\xrightarrow[\alpha]{}Q(y) = ((negQ(y))\xrightarrow[\alpha]{}(negP(x)))$
UE16	$P(x)\xrightarrow{\alpha}Q(y) = ((negQ(y))\xrightarrow{\alpha}(negP(x)))$
LE17	$(P(x)\xrightarrow[\alpha]{}Q(y)) = (negP(x)\underset{\alpha}{\vee}Q(y))$
UE17	$(P(x)\xrightarrow{\alpha}Q(y)) = (negP(x)\overset{\alpha}{\vee}Q(y))$
LE18	$P(x)\xleftrightarrow[\alpha]{}Q(y) = (P(x)\underset{\alpha}{\wedge}Q(y)) \vee (negP(x)\underset{\alpha}{\wedge}negQ(y))$
UE18	$P(x)\xleftrightarrow{\alpha}Q(y) = (P(x)\overset{\alpha}{\wedge}Q(y)) \vee (negP(x))\overset{\alpha}{\wedge}negQ(y))$
ME1	$\tau(P(x)\underset{\alpha}{\wedge}Q(y)) = (negP(x)\overset{1-\alpha}{\vee}negQ(y))$
ME2	$\tau(P(x)\overset{\alpha}{\wedge}Q(y)) = (negP(x)\underset{1-\alpha}{\vee}negQ(y))$
ME3	$\tau(P(x)\underset{\alpha}{\vee}Q(y)) = (negP(x)\overset{1-\alpha}{\wedge}negQ(y))$
ME4	$\tau(P(x)\overset{\alpha}{\vee}Q(y)) = (negP(x)\underset{1-\alpha}{\wedge}negQ(y))$
ME5	$\tau(P(x)\xrightarrow[\alpha]{}Q(y)) = P(x)\overset{1-\alpha}{\wedge}negQ(y)$
ME6	$\tau(P(x)\xrightarrow{\alpha}Q(y)) = P(x)\underset{1-\alpha}{\wedge}negQ(y)$
ME7	$P(x)\xrightarrow[\alpha]{}(Q(y)\xrightarrow[\alpha]{}R(z)) = (P(x)\overset{1-\alpha}{\wedge}Q(y))\xrightarrow[\alpha]{}R(z)$
ME8	$P(x)\xrightarrow{\alpha}(Q(y)\xrightarrow{\alpha}R(z)) = (P(x)\underset{1-\alpha}{\wedge}Q(y))\xrightarrow{\alpha}R(z)$
ME9	$P(x)\xleftrightarrow[\alpha]{}negQ(y) = \tau(P(x)\xleftrightarrow{1-\alpha}Q(y))$
ME10	$P(x)\xleftrightarrow{\alpha}negQ(y) = \tau(P(x)\xleftrightarrow[1-\alpha]{}Q(y))$

4. NORMAL FORMS IN FUZZY PREDICATES THROUGH ROUGH APPROXIMATIONS

In this section,*Disjunctive Normal Form* (DNF), *Conjunctive Normal Form* (CNF), *Principal Disjunctive Normal Form* (PDNF) and *Principal Conjunctive Normal Form* (PCNF) on Fuzzy Predicates under Rough approximations are discussed. Here, for a fuzzy predicate $P(x)$ and a threshold α , $P_{\alpha}(x)$, $\tau(P_{\alpha}(x))$, $(negP(x))_{\alpha}$ and $\tau(negP(x))^{1-\alpha})$ are called the *lowerliterals* of $P_{\alpha}(x)$ and $P^{\alpha}(x)$, $\tau(P^{\alpha}(x))$, $(negP(x))^{\alpha}$ and $\tau(negP(x))_{1-\alpha})$ are called the *upperliterals* of $P^{\alpha}(x)$ .The elementary sum/ product of lower/ upper literals are called as the *lower/upper elementary sum/ product* respectively. L-Disjunctive Normal Form is defined as the elementary sum of lower elementary products; U-Disjunctive Normal Form is defined as the elementary sum of upper elementary products. L-Conjunctive Normal Form is defined as the elementary product of lower elementary sums and U-Conjunctive Normal Form is defined as the elementary product of upper elementary sums. The detailed proofs and illustrations are given in [6].

5. CONCLUSION

In this paper, we described a naïve approximating approach on Fuzzy Predicates through conventional Rough Sets by listing all implication and equivalence rules. Also, we described the normal forms under approximations.

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