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Local Neutrosophic Rough Similarity Measure based tangent function

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Abstract:

This work studies the information brought by the degree of truth, falsity, and indeterminacy Membership in the Neutrosophic set (NS) defined as a vector representation. The tangent similarity measure into the Local Neutrosophic Rough set (LNRS) is proposed by tangent similarity measure for NSs and is also proved with some of its properties and an algorithm is generated for the proposed approach between two LNRS. Further, the proposed similarity measure is validated with the school selection problem.

Keywords: Neutrosophic Set, Local Rough Set, Local Neutrosophic Rough Set, Similarity Measure (SM), Tangent Function.

1. Introduction

In 1988, F. Smarandache [3] presented a new concept named NS. The idea of NS makes imprecise, indeterminate and inconsistent membership degrees independent, while explicitly quantifying indeterminacy. Indeterminacy is a significant factor in many real-world decision-making problems. Zadeh [11] initially invented the fuzzy set (FS) theory, which is used to express uncertainty and incomplete information. Atnassov [10] enhanced the idea of FS, namely Intuitionistic FS (IFS). IFS distinguishes itself by assigning a membership and non-membership degree to every element in the collection. Wang et al [4] initiated the concept of interval valued NS (IVNS). The concept expands the idea of interval valued numbers. The concept of Single Valued Neutrosophic Set (SVNS) was introduced by wang et al [5] as a subset of NS. SVNS have applications in technical and scientific domains. NS, SVNS and IVNS have been researched and used in several areas, including decision making [1], medical diagnosis, image segmentation and so on.

Pawlak [20] developed the Rough Set (RS) concept in 1982. It is formed by two components: equivalence relation and crisp set. Rough Set theory has many applications and can be integrated into other fields. The reconstruction of a classical rough set is defined as a Local Rough Set (LRS). It was initiated by Yuhua Qian [19]. LRS controls limited labeled data, overfitting in attribute reduction and computational ineffectiveness. Rough Neutrosophic Set (RNS) concepts were first introduced by Broumi and F. Smarandache [14]. RNS is defined by using the ideas of NS and RS. The LNRS concept was initiated by S. Bharathi et al [12]. The handling of uncertainty problems is effectively managed by this LNRS tool.

In decision-making scenarios, it is essential to consider the notion of similarity. The literature analysis reveals that several methods have been proposed to determine the level of similarity between NS, SVNS, and IVNS [7, 8]. Ye [7] illustrated the application of similarity metrics utilizing hamming and Euclidean distances to IVNS and presented an instance of decision-making issues. Surapati Pramanik, and K.Mondal [16] suggested using the cosine similarity measure for RNS and also introduced a weighted fuzzy similarity measure based on the tangential function. Surapati Pramanik and K. Mondal [15,8] also introduced tangent SM between IFS and SVNS and investigated some of its properties.

Tangent similarity measures were applied in FS, IFS, NS, IVNS, SVNS and SVBNS. However, there is no investigation combined with the LRS and NS. This work presents the notion of a tangent function based on Local Neutrosophic Rough similarity measure and investigates its properties. This proposed method aims to reduce the attribute and computational time. Further, it demonstrates the proposed approach to the school selection problem.

2. Preliminaries

Definition 2.1 [14]

Let S be non-zero set. Assume Z is a relation of equivalence in S and W be a relation of neutrosophic in S, also truth T_W, indeterminacy I_W , falsity F_W membership function. The upper and lower values of approximation on W, the pair (S,Z) be approximation space defined $\underline{N}(W)$ and $\overline{N}(W)$ are provided below.

$\underline{N}(W) = \{< g, T_{\underline{N}(W)}(g), I_{\underline{N}(W)}(g), F_{\underline{N}(W)}(g) >| \; b \in [g]_Z, g \in S \}$

$\overline{N}(W) = \{< g, T_{\overline{N}(W)}(g), I_{\overline{N}(W)}(g), F_{\overline{N}(W)}(g) >| b \in [g]_Z, g \in S\}$ Where

$T_{\underline{N}(W)}(g) = \wedge_{d\epsilon[g]_Z} T_D(d)$, $I_{\underline{N}(D)}(c) = \wedge_{d\epsilon[c]_Z} I_D(d)$, $F_{\underline{N}(D)}(c) = \wedge_{d\epsilon[c]_Z} F_D(d)$,

$T_{\overline{N}(D)}(c) = \vee_{d\epsilon[c]_Z} T_{(D)}(d)$, $I_{\overline{N}(D)}(c) = \vee_{d\epsilon[c]_Z} I_{(D)}(d)$, $F_{\overline{N}(D)}(c) = \vee_{d\epsilon[c]_Z} F_{(D)}(d)$

Such that $T_{\underline{N}(D)}(c), I_{\underline{N}(D)}(c), F_{\underline{N}(D)}(c), T_{\overline{N}(D)}(c), I_{\overline{N}(D)}(c), F_{\overline{N}(D)}(c) : D\epsilon[0,1]$,

So, $0 \leq T_{\underline{N}(D)}(c) + I_{\underline{N}(D)}(c) + F_{\underline{N}(D)}(c) \leq 3$ *and*

$0 \leq T_{\overline{N}(D)}(c) + I_{\overline{N}(D)}(c) + F_{\overline{N}(D)}(c) \leq 3.$

where symbols "∧" and" ∨" means maximum and minimum operators respectively. Where $[c]_Z$ is equivalence class in Z. Then $(\underline{N}(D), \overline{N}(D))$ is defined as Rough Neutrosophic set in (S,Z).

Definition 2.2 [19]

Let (S,Q) being a space of approximations. Let D be an including degree in $P(S) \times P(S)$. If any $F \subseteq S$, the β – lower, γ- upper approximations are as follows

$\underline{Q}_\alpha(F) = \{f | D\,(F/\,[q]_Q \;\geq\; \alpha, f \in F\}$,

$\overline{Q}_\beta(F) = \{f | D\,(F/\,[q]_Q > \;\beta, f \in F\}$. This pair $(\underline{Q}_\alpha(F), \overline{Q}_\beta(F))$ is defined as LRS.

Definition 2.3 [12]

Let (W,R) be a space of approximation, W be non-zero set and R be a relation of equivalence in W. Let K be a neutrosophic rough set on W, defined by membership τ_K, indeterminacy δ_K and non-membership η_K . Let $0 \leq \beta < \alpha \leq 1$ at some $K\epsilon W$, the local α – lower and local β - upper approximations are defined as $\underline{N}_\alpha(K)$ *and* $\overline{N}_\beta(K)$ in W respectively. Define

$\underline{N}_\alpha(K) = \{(l, D(\left(\tau_{\underline{N}_\alpha(K)}(l), \delta_{\underline{N}_\alpha(K)}(l), \eta_{\underline{N}_\alpha(K)}(l)\right)/[l]_R)) \;\geq\; \alpha \mid l \in W,$

$[l]_R \neq \emptyset\}$

$\overline{N}_\beta(K) = \{(l\,, D((\tau_{\overline{N}_\beta(K)}(l)\,, \delta_{\overline{N}_\beta(K)}(l)\,, \eta_{\overline{N}_\beta(K)}(l))/[l]_R)) \;>\; \beta \mid l \in W\,, [l]_R \neq \emptyset\,\}$, where

$\tau_{\underline{N}_\alpha(K)}(l) = min_{m\in[l]_R}\tau_K(m) \quad, \delta_{\underline{N}_\alpha(K)}(l)$

$= max_{m\in[l]_R}\delta_K(m) \quad, \eta_{\underline{N}_\alpha(K)}(l) = max_{m\in[l]_R}\eta_K(m) \quad,$

$\tau_{\overline{N}_\beta(K)}(l) = max_{m\in[l]_R}\tau_K(m) \quad, \delta_{\overline{N}_\beta(K)}(l)$

$= min_{m\in[l]_R}\delta_K(m) \quad, \eta_{\overline{N}_\beta(K)}(l) = min_{m\in[l]_R}\eta_K(m)$

Here $\tau_K(l), \delta_K(l), \eta_K(l)$ denoted as membership, indeterminacy & non membership of l in K.Therefore

$0 \leq \tau_{\underline{N}_\alpha(K)}(l) + \delta_{\underline{N}_\alpha(K)}(l) + \eta_{\underline{N}_\alpha(K)}(l) \leq 3\,,$

$0 \leq \tau_{\overline{N}_\beta(K)}(l) + \delta_{\overline{N}_\beta(K)}(l) + \eta_{\overline{N}_\beta(K)}(l) \leq 3$. The functions

$\tau_{\underline{N}_\alpha(K)}(l), \delta_{\underline{N}_\alpha(K)}(l), \eta_{\underline{N}_\alpha(K)}(l), \tau_{\overline{N}_\beta(K)}(l) + \delta_{\overline{N}_\beta(K)}(l) + \eta_{\overline{N}_\beta(K)}(l) : K \rightarrow]0^-, 1^+[$.

The pair $(\underline{N}_\alpha(K)\,, \overline{N}_\beta(K))$ called LNRS in W.

3. Local Neutrosophic Rough Similarity Measure on the basis of Tangent Function

Definition 3.1

Consider $\underline{T}_{LNRS\,(K,L)} = \{x_p, \underline{\tau}_{(K,L)}(x_p), \underline{\delta}_{(K,L)}(x_p), \underline{\eta}_{(K,L)}(x_p)\}$

$\overline{T}_{LNRS\,(K,L)} = \{x_p, \overline{\tau}_{(K,L)}(x_p), \overline{\delta}_{(K,L)}(x_p), \overline{\eta}_{(K,L)}(x_p)\}$

$\underline{T}_{LNRS\,(K,L)}, \overline{T}_{LNRS\,(K,L)}$ are two lower and upper LNRS. Here τ, δ, η are the truth, indeterminate and incompatible membership values. The similarity measure of LNRS established with tangent function only on the direction of two vectors, and omits the effect of distance between those vectors. It can be represented as follows.

$$T_{LNRS(K,L)} = \frac{1}{n}\sum_{p=1}^{n} 1 - \tan\left[\frac{\pi|\tau_K(x_p)-\tau_L(x_p)|+|\delta_K(x_p)-\delta_L(x_p)|+|\eta_K(x_p)-\eta_L(x_p)|}{12}\right] \qquad (3.1)$$

$$\tau_K(x_p) = \frac{\underline{\tau}_{(K)}(x_p)+\overline{\tau}_{(K)}(x_p)}{2}, \tau_L(x_p) = \frac{\underline{\tau}_{(L)}(x_p)+\overline{\tau}_{(L)}(x_p)}{2}$$

$$\delta_K(x_p) = \frac{\underline{\delta}_{(K)}(x_p)+\overline{\delta}_{(K)}(x_p)}{2}, \delta_L(x_p) = \frac{\underline{\delta}_{(L)}(x_p)+\overline{\delta}_{(L)}(x_p)}{2}$$

$$\eta_K(x_p) = \frac{\underline{\eta}_{(K)}(x_p)+\overline{\eta}_{(K)}(x_p)}{2}, \eta_L(x_p) = \frac{\underline{\eta}_{(L)}(x_p)+\overline{\eta}_{(L)}(x_p)}{2}.$$

Preposition 3.2

The LNRS is based on the tangent similarity measure with truth, indeterminate and incompatible function $T_{LNRS(K,L)}$ which satisfies the conditions as follows.

I. $0 \leq T_{LNRS(K,L)} \leq 1$
II. $T_{LNRS(K,L)} = 1$ iff $K = L$
III. $T_{LNRS(K,L)} = T_{LNRS(L,K)}$
IV. Let M be a LNRS and $K \subset L \subset M$ then $T_{LNRS(K,M)} \leq T_{LNRS(K,L)}$ and $T_{LNRS(K,M)} \leq T_{LNRS(L,M)}$.

Proof

1. As known, truth, indeterminate and incompatible membership functions lie in $[0,1]$ and the value of tangent function also lies between $[0,1]$. Then the tangent similarity measure also lies between $[0,1]$.

Therefore, consequently $0 \leq T_{LNRS(K,L)} \leq 1$.

2. For any pair K and L in LNRS, if $K = L$ then $\tau_K(x_p) = \tau_L(x_p)$, $\delta_K(x_p) = \delta_L(x_p)$, $\eta_K(x_p) = \eta_L(x_p)$.

Also,

$|\tau_K(x_p) - \tau_L(x_p)| = 0$, $|\delta_K(x_p) - \delta_L(x_p)| = 0$,

$|\eta_K(x_p) - \eta_L(x_p)| = 0$

Therefore $T_{LNRS(K,L)} = 1$.

Conversely, assume $T_{LNRS(K,L)} = 1$, then

$|\tau_K(x_p) - \tau_L(x_p)| = 0$, $|\delta_K(x_p) - \delta_L(x_p)| = 0$, $|\eta_K(x_p) - \eta_L(x_p)| = 0$

Which implies that $\tau_K(x_p) = \tau_L(x_p)$, $\delta_K(x_p) = \delta_L(x_p)$, $\eta_K(x_p) = \eta_L(x_p)$. Thus $K = L$.

3. From definition 3.1,

$$T_{LNRS(K,L)} = \frac{1}{n}\sum_{p=1}^{n} 1 - \tan\left[\frac{\pi|\tau_K(x_p)-\tau_L(x_p)|+|\delta_K(x_p)-\delta_L(x_p)|+|\eta_K(x_p)-\eta_L(x_p)|}{12}\right]$$

$$= \frac{1}{n}\sum_{p=1}^{n} 1 - \tan\left[\frac{\pi|\tau_L(x_p)-\tau_K(x_p)|+|\delta_L(x_p)-\delta_K(x_p)|+|\eta_L(x_p)-\eta_K(x_p)|}{12}\right]$$

$T_{LNRS(K,L)} = T_{LNRS(L,K)}$.

4. If $K \subset L \subset M$ then $\tau_K(x_p) \leq \tau_L(x_p) \leq \tau_M(x_p)$, $\delta_K(x_p) \geq \delta_L(x_p) \geq \delta_M(x_p)$ and $\eta_K(x_p) \geq \eta_L(x_p) \geq \eta_M(x_p)$.

Which implies the following inequalities,

$|\tau_K(x_p) - \tau_L(x_p)| \leq |\tau_K(x_p) - \tau_M(x_p)|$, $|\tau_L(x_p) - \tau_M(x_p)| \leq |\tau_K(x_p) - \tau_M(x_p)|$,

$|\delta_K(x_p) - \delta_L(x_p)| \geq |\delta_K(x_p) - \delta_M(x_p)|$, $|\delta_L(x_p) - \delta_M(x_p)| \geq |\delta_K(x_p) - \delta_M(x_p)|$,

$|\eta_K(x_p) - \eta_L(x_p)| \geq |\eta_K(x_p) - \eta_M(x_p)|$, $|\eta_L(x_p) - \eta_M(x_p)| \geq |\eta_K(x_p) - \eta_M(x_p)|$.

Hence $T_{LNRS(K,M)} \leq T_{LNRS(K,L)}$ and

$T_{LNRS(K,M)} \leq T_{LNRS(L,M)}$.

4. Algorithm for the proposed method

Let the attribute $Z_i = \{z_1, z_2, \ldots z_c\}$ and let $H_j = \{h_1, h_2, \ldots h_q\}$ be the criteria. To calculate the decision making for all attributes $Z_i\{i = 1,2, \ldots c\}$ corresponding to alternatives $G_d\{d = 1,2, \ldots e\}$ based on LNRS. We can create a decision matrix by utilizing all of the evaluation data provided by the decision makers for each choice. The algorithm for the proposed method is as follows.

Step:1 Formulate the decision matrix between attributes and criteria by applying LNRS. It can be denoted as below.

	z_1	z_2	…	z_c
h_1	$\underline{s}11(h_1,z_1), \overline{s}11(h_1,z_1)$	$\underline{s}12(h_1,z_2), \overline{s}12(h_1,z_2)$	…	$\underline{s}1c(h_1,z_c), \overline{s}1c(h_1,z_c)$
h_2	$\underline{s}21(h_2,z_1), \overline{s}21(h_2,z_1)$	$\underline{s}22(h_2,z_2), \overline{s}22(h_2,z_2)$	…	$\underline{s}2c(h_2,z_c), \overline{s}2c(h_2,z_c)$
…	…	…	…	…
h_q	$\underline{s}q1(h_q,z_1), \overline{s}q1(h_q,z_1)$	$\underline{s}q2(h_q,z_2), \overline{s}q2(h_q,z_2)$	…	$\underline{s}qc(h_q,z_c), \overline{s}qc(h_q,z_c)$

Table:1

Step: 2 Formulate the decision matrix between attributes and alternatives.

	g_1	g_2	…	g_m
z_1	$\underline{s}11(z_1,g_1), \overline{s}11(z_1,g_1)$	$\underline{s}12(z_1,g_2), \overline{s}12(z_1,g_2)$	…	$\underline{s}1m(z_1,g_m), \overline{s}1m(z_1,g_m)$
z_2	$\underline{s}21(z_2,g_1), \overline{s}11(z_2,g_1)$	$\underline{s}22(z_2,g_2), \overline{s}22(z_2,g_2)$	…	$\underline{s}2m(z_2,g_m), \overline{s}2m(z_2,g_m)$
…	…	…	…	…
z_c	$\underline{s}c1(z_c,g_1), \overline{s}c1(z_c,g_1)$	$\underline{s}c2(z_c,g_2), \overline{s}c2(z_c,g_2)$	…	$\underline{s}cm(z_c,g_m), \overline{s}cm(z_c,g_m)$

Table:2

Step: 3 Computation of the lower approximation (LA) and upper approximation (UA) utilizing LNRS. For $n = 1$ to k.

I. Compute $[A_n]_R$ of A_n, $A_n \epsilon A, A$ is the universal set. //Calculating the equivalence classes.

II. Find the inclusion degree

Fix the value of α and β. If $D(A/[A_n]_R) \geq \alpha$

Then $LA \cup \{A_n\} \to LA, n \to n + 1$. And $D(A/[A_n]_R) < \beta$

Then $UA \cup \{A_n\} \to UA$

Step: 4 Finding the tangent similarity measure between attributes and alternatives

Calculate the tangent similarity measure based on lower and upper approximation from Table 1 and Table 2.

Step: 5 Priority of the alternatives

The calculated measure value is sorted in ascending order. The priority that has the highest measure value is the most appropriate alternative.

5. Demonstration of proposed approach

This section demonstrates the LNRS strategy with the utilization and efficiency of the proposed approach. Let's examine the following problem in decision making. This assumes that the three parents can provide their children with a proper education at an appropriate school. They select three schools for their kids to get admission. Assume that there are three parents $P = \{p_1, p_2, p_3\}$, S = {Montessori school, International school, Matriculation school, CBSE School, Private public school} be a set of schools. The following five criteria require the parent to make a decision. B = {Financial health, Quality of education, Transportation, Sports and other activities, Environment and Safety concerns}. Parents can make decisions by using the following LNRS approach.

Let the attribute $Q = \{d_1, d_2, d_3, d_4, d_5\}$ be a universal set. The equivalence classes of the attributes are $\{d_1, d_2\}, \{d_3, d_4\}, \{d_5\}$ and $X = \{d_1, d_2, d_4\}$. Assume that the parameter $\alpha = 0.6$ and $\beta = 0.2$. Here the attribute is defined as

$Q = \{$ Financial health, Quality of education, Transportation,

Sports and other activities, Environment and Safety concerns$\}$ respectively

The following table shows that the relationship is based on parents and their criteria.

Q	Financial health	Quality of education	Transportation	Sports and other activities	Environment and Safety concern
p_1	$(.2,.4,.4)$ (.6, .2, .2)	$(.2,.6,.4)$ (.4, .4, .2)	$(.8,.1,.1)$ (.8, .1, .3)	$(.5,.2,.3)$ (.7, .4, .1)	$(0,.8,.4)$ (.2, .6, .2)
p_2	$(.9,.1,.1)$ $(.9,.1,.1)$	$(.8,.2,.1)$ (.6, .2, .3)	$(.2,.7,.2)$ (.2, .7, .2)	$(.6,.2,.2)$ (.8, .2, .2)	$(.8,.1,.2)$ (.8, .1, .2)
p_3	$(.6,.4,.1)$ (. 8,.2, .1)	$(.6,.4,.2)$ (.4, .2, .2)	$(.3,.6,.3)$ (.5, .4, .1)	$(.5,.1,.4)$ (.5, .1, .6)	$(.2,.8,.1)$ (.4, .6, .1)

Table:3

The following table presents the relationship between the criteria and their respective schools.

Relation	Montessori school	International school	Matriculation school	CBSE School	Private public school
Financial health	$(.8,.2,0)$ (.4, .6, .2)	$(.2,.5,.3)$ (.6, .3, .3)	$(.9,.1,0)$ (.9, .1, 0)	$(.1,.6,.3)$ (.7, .2, .1)	$(.6,.2,.2)$ (.2, .8, .2)
Quality of education	$(.7,.1,.2)$ $(.7,.3,.2)$	$(.3,.7,0)$ (.5, .3, .2)	$(.7,.2,.1)$ (.1, .6, .5)	$(.2,.6,.2)$ (.8, .4, 0)	$(.5,.3,.2)$ (.7, .1, .4)
Transportation	$(.2,.6,.2)$ (. 8,.2, .2)	$(.8,.1,.1)$ (.6, .3, .3)	$(.3,.5,.2)$ (.5, .3, .4)	$(.3,.7,0)$ (.7, .1, .4)	$(.8,.1,.1)$ (.2, .7, .3)
Sports and other activities	$(.5,.3,.2)$ $(.3,.5,.4)$	$(.4,.3,.3)$ (.2, .7, .5)	$(.5,.4,.1)$ (.3, .8, .5)	$(.3,.6,.1)$ (.7, .2, .3)	$(.7,.1,.2)$ (.3, .1, .2)
Environment and Safety concern	$(.2,.5,.3)$ (. 4,.3, .7)	$(.1,.7,.2)$ (.3, .3, .2)	$(.8,.1,.1)$ (.2, .1, .3)	$(.6,.1,.3)$ (.2, .3, .3)	$(.5,.1,.4)$ (.3, .3, .4)

Table:4

To determine the upper and lower approximations by using LNRS.

$[d_1]_R = \{d_1, d_2\},\ [d_2]_R = \{d_1, d_2\},\ [d_4]_R = \{d_3, d_4\}$

$D(X/[d_1]_R) = \frac{2}{3}, D(X/[d_2]_R) = \frac{2}{3}, D(X/[d_4]_R) = \frac{1}{3}.$

$\underline{T}_{0.6}(X) = \{d_1, d_2\}$

$\overline{T}_{0.2}(X) = [d_1]_R \cup [d_2]_R \cup [d_4]_R, \overline{T}_{0.4}(X) = \{d_1, d_2, d_3, d_4\}.$

Reduce the attributes in Tables 3 and 4 using these lower and upper approximations. Further, apply these values in equation (3.1) with a reduction of the attributes. Table 5 determines the tangent similarity measure for selecting a suitable school.

LNRS similarity measure	Montessori School	International School	Matriculation School	CBSE School	Private Public School
p_1	0.7698	**0.8337**	0.7466	0.8017	0.8028

p_2	0.7848	0.7315	**0.8172**	0.7644	0.8078
p_3	**0.8124**	0.8020	0.7798	0.7911	0.8028

Table:5

The greatest similarity measure in Table 5 is the decision to select a proper school. Thus, parent p_1 can select an International school, the parent p_2 can select Matriculation school, parent p_3 can select Montessori School.

6. Comparative analysis

The effectiveness of the proposed LNRS approach based on tangent function is illustrated through a comparison with the existing similarity measures of cosine, cosecant, and tangent logarithmic distance of RNS were discussed in [2, 16]. They are listed below.

Cosine SM of RNS [16]

$$C_{RNS}(K,L) = \frac{1}{n}\sum_{f=1}^{n}\frac{\omega T_K(x_f)\omega T_L(x_f)+\omega I_K(x_f)\omega I_L(x_f)+\omega F_K(x_f)\omega F_L(x_f)}{\sqrt{(\omega T_K(x_f))^2+(\omega I_K(x_f))^2+(\omega F_K(x_f))^2}\ \sqrt{(\omega T_L(x_f))^2+(\omega I_L(x_f))^2+(\omega F_L(x_f))^2}} \quad (6.2)$$

Tangent logarithmic distance and cosecant SM of RNS [2]

I. $$TLD_{RNS}(K,L) = \frac{1}{2(n+1)}[\sum[\tan(\log(1+|\underline{\tau}_K(x_p)-\underline{\tau}_L(x_p)|+|\underline{\delta}_K(x_p)-\underline{\delta}_L(x_p)|+|\underline{\gamma}_K(x_p)-\underline{\gamma}_L(x_p)|+|\overline{\tau}_K(x_p)-\overline{\tau}_L(x_p)|+|\overline{\delta}_K(x_p)-\overline{\delta}_L(x_p)| \quad (6.3)$$

II. $$COSEC_{RNS}(K,L) = \frac{1}{5n}[\sum COSEC[\frac{(\pi(1+X+Y))}{4n}]]. \quad (6.4)$$

Applying these three equations (6.2,6.3,6.4), without attribute reduction and diagnosing the three patients suffering from viral fever [2, 16]. The proposed approach involving attribute reduction should be utilized to address the challenge of achieving an accurate diagnosis. This reduction reduces computational time while also making it more deterministic. Using lower and upper approximations to reduce the attribute in the given problem [2, 16]. The highest values are obtained, for the patients suffering from viral fever.

Conclusion

This paper describes tangent SM and proves some of its properties. The utility of this proposed method is that it reduces the computational time. Also, we provided a comparative study of the current approaches. Further, an application was given to the proposed method, that provides parents to select suitable schools for their kids for proper education. In future the proposed concept can be applied in clustering analysis and medical diagnosis.

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