From fuzzification to neutrosophication:A better interface between logic and human reasoning

Swati Aggarwal, Ranjit Biswas
Computer Science and Engg.
itm University
Gurgaon,India
swati1178@gmail.com

A.Q.Ansari
Electrical Engineering
Jamia Milia Islamia
New Delhi, India

***Abstract* -- Prof. L. A. Zadeh recognized that to simulate soft knowledge of human reasoning it is essential to use some formal approach to knowledge processing. So he pioneered by taking first step by proposing a novel logic, fuzzy logic in 1965, by releasing constraints imposed on existing formalisms to accommodate important properties of natural inference [15]. This paper targets human reasoning domain; lists the limitations of fuzzy logic in this area and suggests a new logic: neutrosophic logic. Experimental data is provided by showing the comparison between fuzzy classifier and neutrosophic classifier, finally paper is concluded with a proposal that neutrosophic logic is a better candidate to simulate human reasoning.**

Keywords-fuzzy logic;human reasoning; neutrosophic logic

I. Fuzzy logic and it's problems

In an attempt to formalize human inference Prof. Zadeh pioneered by relaxing constraints imposed by classical logic, in which gradual numerical degree of membership is permitted. Contrary to "crisp logic", where binary sets have binary logic, fuzzy logic variables may have a truth value that ranges between 0 and 1 and is not constrained to the two truth values of classic propositional logic[2], [15]. The basic impetus for such relaxations is clear as the environment in which natural inference takes place is full of uncertainties and assertions which are completely true or false are very rare; fuzzy logic attempts to capture valid reasoning patterns about uncertainty [12],[13].

Prof. Zadeh had aptly realized that it is imperative to have a decent model of semantics of human concepts and perform realistic operations than to have an awful model and perform verifiably correct operations. Introduction of fuzzy systems led making of systems which exhibit human concepts and their formalization; and thus this stimulated enormous research activity in soft knowledge processing [14]. Though fuzzy logic concepts accounts for the nature of human concepts but they are still limited as they cannot cater to human concepts which are developed and modified in open world, as formal concepts are fixed in closed world[5]. So it is quite natural that for open domain problems like open world of human fuzzy concepts, rigidities of fuzzy formal approach be further relaxed.

Consider this example:

If X is cold then it is very likely that Y is hot.
If X is hot then it is not likely that Y is hot.
What is the probability that Y is hot if X is having medium temperature?

This example gives a clear insight for conventional human reasoning systems, fuzzy reasoning systems and futuristic human reasoning systems.

Conventional human reasoning systems fail in four aspects [4]:

(1) Such systems do not offer any method for dealing with the fuzziness of antecedents and consequents.

(2) For such systems probabilities can be estimated as crisp numbers.

(3) No mechanism for inference from rules in which the qualifying probabilities are fuzzy.

(4) Finally, rules which are used for composition of probabilities depend on unsupported assumptions about conditional independence.

Fuzzy logic overcomes some but not all the limitations of conventional human reasoning system to certain extend [1], [13]:

(1) Fuzzy logic permits the antecedents and/or consequents and/or qualifying probabilities to be fuzzy.

(2) Fuzzy logic also makes it possible to estimate probabilities as fuzzy rather than crisp numbers.

Apart from the benefits of fuzzy logic, futuristic human reasoning models needs to address two very significant aspects, and they are [5]:

978-0-7695-4246-1/10 $26.00 © 2010 IEEE
DOI 10.1109/ICETET.2010.26

a. The composition of qualifying probabilities can lead to fuzzy probabilities that are inadequately precise or, equally, unsatisfactorily informative.

b. Normally inference in fuzzy logic reduces; in general, to the solution of a nonlinear program, so devising techniques for the solution of such programs may be computationally pricey. Currently we do not have inexact, low-priced techniques for inference from fuzzy-probability qualified fuzzy if-then rules. Also we do not have an effective method of inference from possibility-qualified rules within a branch.

Reviewing all these points it appears that fuzzy logic is not the final solution for representing human knowledge about the world; rather it is a foundation based on established notions that could easily be grasped by engineers and researchers alike as a step toward formalizing human reasoning. Goal of the model that reasons human concepts should be that it can take partially true facts which have the element of uncertainty, vagueness, ambiguity, imprecision, undefined, unknown, incompleteness, inconsistency, redundancy or contradiction; which are distributed over a sample space, and build a knowledge-based system that will apply certain reasoning and aggregation strategies to make useful decisions [3]. So it is quite expected that some more barriers be lifted from fuzzy logic before it can be applied to delicate areas of fuzzy reasoning. Till the time laws of human reasoning are understood, accommodation of paradoxes should be a crucial aspect of human reasoning model; as experimentation with the model would extend the understanding and will help to resolve them.

II. WHY NEUTROSOPHIC LOGIC IS NEEDED?

Quite recently, Neutrosophic Logic has been proposed by Florentine Smarandache which is based on non-standard analysis that was given by Abraham Robinson in 1960s [6], [9]. Neutrosophic Logic was developed to represent mathematical model of uncertainty, vagueness, ambiguity, imprecision, undefined, unknown, incompleteness, inconsistency, redundancy, contradiction present in the data[7],[9].

All the factors stated are very integral to human thinking, as it is very rare that we tend to conclude/judge in definite environments, imprecision of human systems could be due to the imperfection of knowledge that human receives (observation) from the external world [7],[8]. Imperfection leads to a doubt about the value of a variable, a decision to be taken or a conclusion to be drawn for the actual system. Multiple factors could lead to uncertainty like incomplete knowledge (ignorance of the totality, limited view on a system because of its complexity), stochasticity (the case of intrinsic imperfection where a typical and single value does not exist), or the acquisition errors (intrinsically imperfect observations, the quantitative errors in measures) [9], [10].
So the developed system would have unknown features and behaviors associated, and there would always be unanticipated happening conditions which are uncontrollable - we mean the indeterminacy plays a role as well; a better approach would be the Neutrosophic Model as discussed.

III. BASICS OF NEUTROSOPHIC LOGIC AND COMPARISON TO FUZZY LOGIC

Let T, I, F be real standard or non-standard subsets of ┤-0, 1+├

with sup $T = t\_sup$, inf $T = t\_inf$,

sup $I = i\_sup$, inf $I = i\_inf$,

sup $F = f\_sup$, inf $F = f\_inf$,

and $n\_sup = t\_sup+i\_sup+f\_sup$,

$n\_inf = t\_inf+i\_inf+f\_inf$.

Let U be a universe of discourse, and M a set included in U. An element x from U is noted with respect to the set M as $x(T, I, F)$ and belongs to M in the following way:

it is $t\%$ true in the set, $i\%$ indeterminate (unknown if it is) in the set, and $f\%$ false, where t varies in T, i varies in I, f varies in F [7], [8], [9].

To summarize following reasons are the major driving force for extending fuzzy logic:

a. Because a paradox, as proposition, cannot be described in fuzzy logic.

For example a paradox is a proposition which is true and false in the same time, Neutrosophic logic representation for the same would be NL (paradox) = (1, i, 1), but this notation is not applicable to fuzzy logic , because if FL(paradox) = 1 (the truth) then automatically the fuzzy component of falsity is 0. That's why neutrosophics is fascinating to study.

b. Neutrosophic logic clearly distinguishes between 'relative truth' and an 'absolute truth', while fuzzy logic does not.

Basically, neutrosophic logic is a generalization of fuzzy logic based on neutrosophy [10]. A proposition is t true, i indeterminate, and f false, where t, i, and f are real values from the ranges T, I, F, with no restriction on T, I, F, or the sum $n=t+i+f$.

Compared with all other logics, neutrosophic logic introduces a percentage of "indeterminacy" - due to the unexpected parameters hidden in some propositions. It also allows each component *t, i, f* to "boil over" 100 or "freeze" under 0.

IV. FUZZY CLASSIFIER VS. NEUTROSOPHIC CLASSIFER

This paper gives a comparison between fuzzy classifier and neutrosophic classifier. For simulations iris dataset (http://archive.ics.uci.edu/ml/datasets/Iris) has been used. All experiments have been carried out on MATLAB 7.0. Iris dataset consists of 4 attributes; sepal length, sepal width, petal length and petal width and is having 150 instances which are categorised into 3 classes; iris-setosa, iris-versicolor and iris-virginica. 30 instances from each class have been used for training (for making rule set) and 20 from each class have been used for testing.

V. EXAMPLE : WHAT WE SUGGEST?

As mentioned above that this paper utilizes iris dataset which is simulated using MATLAB 7.0. Currently MATLAB does not provide with the facility of neutrosophication [11], so to simulate it, three FIS have been created with the name of iris-t, iris-i, iris-f, representing true, indeterminate and false value.

This paper represents the working of mamdani type FIS. To represent the neutrosophication process and working of this paper it is essential to show the fuzzy counterpart of the same.

Fuzzy classifier uses membership functions for each attribute. Fig. 1,2,3 shows membership function for sepal length, iris classes and rule viewer details for 142nd instance.

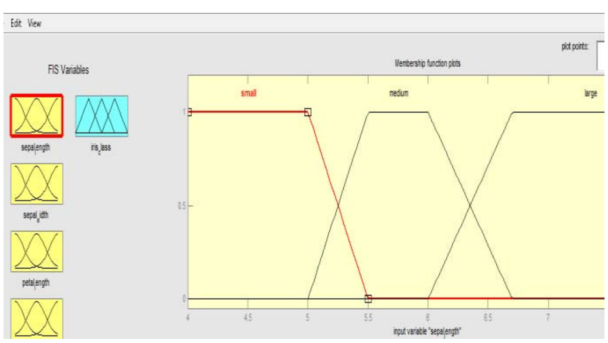

Fig.1 Membership function for sepal length

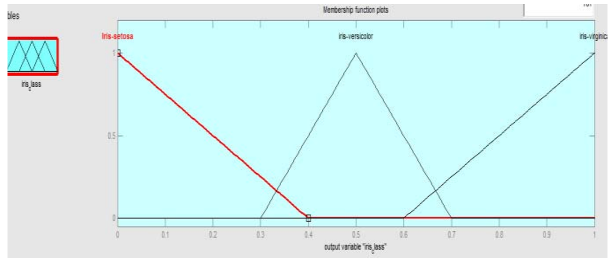

Fig. 2 Membership function for iris classes

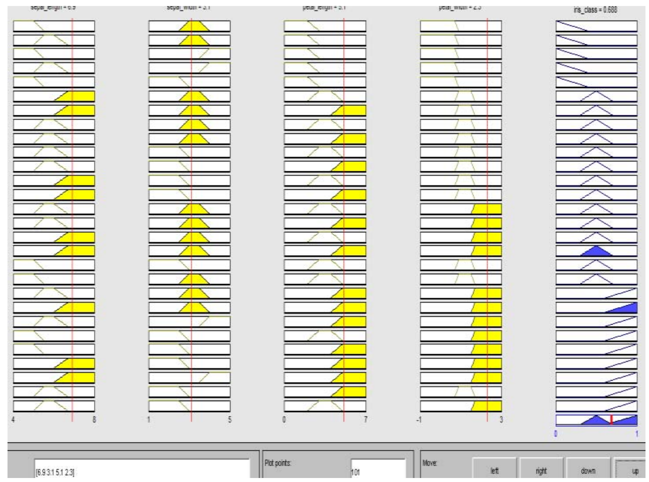

Fig. 3 Rule viewer details for 142nd instance (6.9, 3.1,5.1, 2.3) giving defuzzified value of 0.688.

There are following observations:

i. Due to the inherent nature of fuzzy logic there is necessary overlapping of the membership functions as depicted in figure 1, 2 [2],[15].

ii. Defuzzified value of 142nd entry is 0.688 which lies in the overlapping range of versicolor and virginica, this indicates that 142nd entry is related to both classes with varying degree of membership function. Similar observation was recorded for following instances; 84,86,88,91,131,133-146,147-150.

So it can be generalized that outputs generated after defuzzification by FIS can be of two types:

Case a. When the output clearly lies in one of the output class.

Case b. Defuzzified value belongs to the overlapping range.

When output belongs to case a, then it is 100% sure that it belongs to a specific class, as for example 31st instance generates defuzzied value of 0.13, that indicates it's association with iris-setosa. But when output belongs to case b, as shown in the figure then it lies in the indeterminacy range where the output value belongs to multiple classes with varying degree of membership [2], [15].

This paper targets that multiple belonginess to multiple classes. It has been suggested on the lines of neutrosophic logic that instead of giving one defuzzified value, output value would take the neutrosophic format of the type Output(true, indeterminacy, false). So applications where in exact membership to a class is required, then it is essential to code using neutrosophic logic.

Next we discuss neutrosophic classifier, figure 4,5,6 and 7,8,9 represents the iris-true FIS (iris-t) and iris-indeterminate (iris-i) FIS respectively. They will generate true and indeterminate components respectively of neutrosophic triplet. On same lines iris-false (iris-f) was also designed, that gives third component of the neutrosophic triplet.

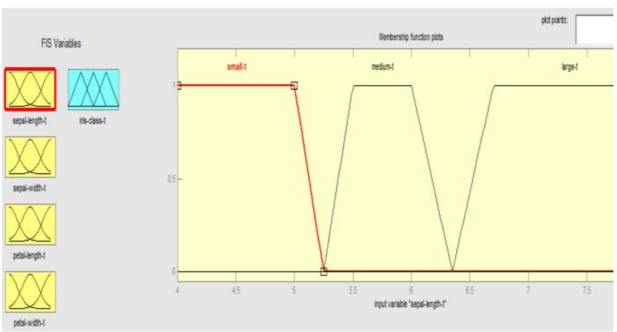

Fig. 4 True membership function for sepal length, represented as sepal-length-t

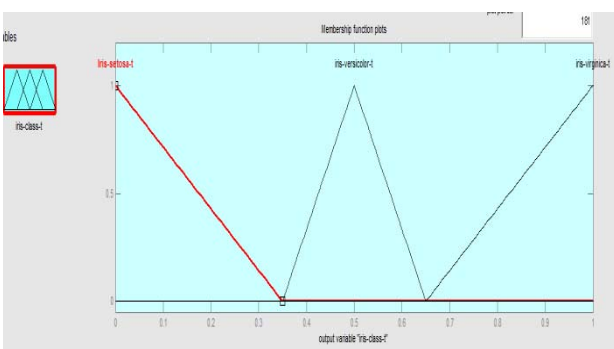

Fig. 5 True membership function for iris classes, represented as iris-class-t

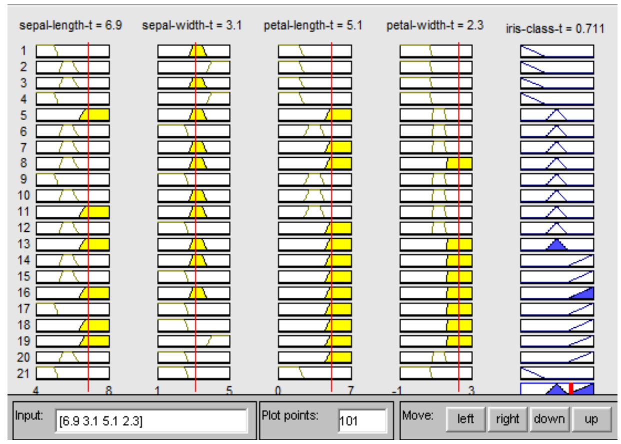

Fig.6 Rule viewer details for 142[nd] instance (6.9, 3.1,5.1, 2.3) giving deneutrosophied value of 0.711

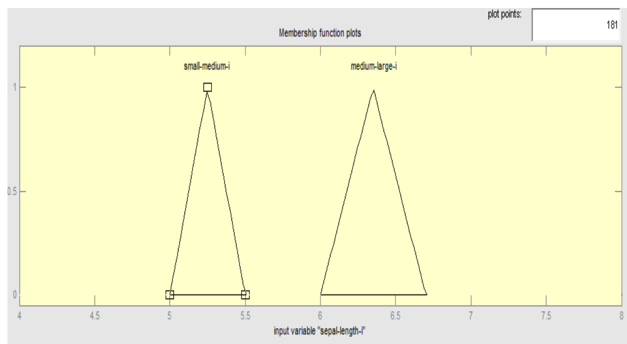

Fig.7 Indeterminate membership function for sepal length, represented as sepal-length-i

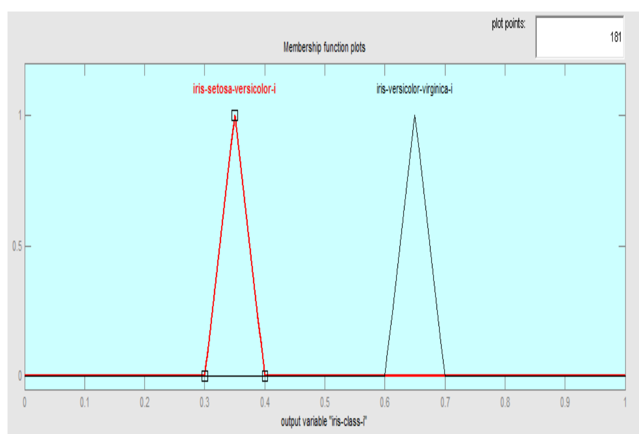

Fig.8 Indeterminate membership function for iris classes, represented as iris-class-i

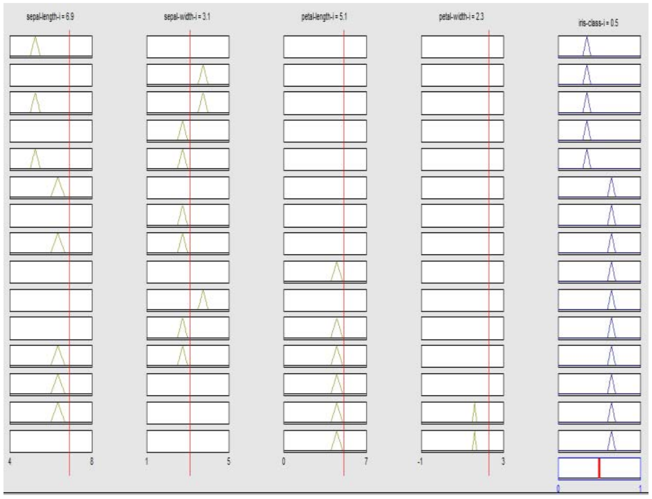

Fig.9 Rule viewer details for 142nd instance (6.9, 3.1,5.1, 2.3) giving deneutrsophied value of 0.5

There are following observations:

i. Membership functions for iris-t have been designed in such a way that there is no overlapping between two membership functions. Like in iris (which uses fuzzification) sepal length for example from 5-5.5 cms there is overlapping of small(4-5.5) and medium classes(5-6.7), 5.25 being the mid point where the degree of membership is same for both classes. This overlapping is nullified in iris-t where small and medium range is fixed as 4-5.25 and 5.25-6.35, as shown in figure 4. Same has been done for iris class membership function in iris-t, as shown in figure 5.

ii. Deneutrosophied value of 142nd entry for iris-t is 0.711 which lies clearly in iris-virginica, as shown in figure 6. Similar correct results were recorded for following instances; 84,86,88,91,131,133-146,147-150.

iii. For iris-i, that represents indeterminate component of neutrosophication process, membership functions have been designed only for the range where there was overlapping, say for example in sepal-length overlapping was from 5-5.5, so small-medium-i membership function is designed that captures the indeterminacy spanned in this region for sepal-length-i, as shown in figure 7. Same has been done for iris class membership function in iris-i, as shown in figure 8.

iv. Deneutrosophied value of 142nd entry for iris-i is 0.5 that clearly indicates that for this entry there is no indeterminacy associated with it. Following indeterminacies were recorded for following instances:

   a. 32,33,40,99 gave indeterminacy of setosa-versicolor-i=0.35

   b. 87-90,92,96,137-139,147-149 gave indeterminacy of versicolor-virginica-i=0.65

v. Same results were recorded for iris-f (false component of neutrosophic component). Membership functions for iris-f were designed similar to iris-i, but with a difference that height of all the membership functions is 0.5.

So for 142nd entry deneutrosophied value is (0.711,0.5,0.5) which is interpreted as (0.711 degree of membership in iris class virginica, zero indeterminacy, zero falsity), as 0.5 value is not spanned by any of the designed indeterminacy or falsity functions.

VI. CONCLUSION

For the statements which have multiple interpretations, each having varying degree of truth associated with it then it is suggested that neutrosophied output is the better representation estimate for such values. Such neutrosophied values are clearly more closer to human mind interpretations as, human brain certainly in this situation cannot generate precise answers in terms of yes or no, as indeterminacy is the sector of unawareness of a proposition’s value, between truth and falsehood; undoubtedly neutrosophic components best fits in the modeling of simulation of human brain reasoning.

REFERENCES

[1] D. Dubois, H. Prade, and J. Lang, “Fuzzy Sets in Approximate Reasoning,” FuzzySets and Systems, Vol. 40, No. 1, March 1991. pp. 143-244.

[2] D. Dubois, H. Prade, and R.R. Yager, eds.,Readings in Fuzzy Sets for Intelligent Systems,Morgan Kaufmann, San Francisco,Calif., 1993.

[3] E.T. Jaynes, “How Does the Brain do Plausible Reasoning?’ Tech. Report 42 I , Microwave Laboratory, Stanford Univ., 1957.

[4] H. Farreny, H. Prade, and E. Wyss, “Approximate Reasoning in a Rule-Based Expert System Using Possibility Theory: A Case Study,” Proc. Information Processing’86, North-Holland, Amsterdam, 1986, pp. 407-413.

[5] H.R. Berenji et al., “A Hierarchical Approach to Designing Approximate Reasoning-Based Controllers for Dynamic Physical Systems,” in Uncertainty in Artificial Intelligence, P.P. Bonissone et al, eds. North-Holland, Amsterdam, 1991, pp. 331-343.

[6] F. Smarandache (1999), Linguistic Paradoxists and Tautologies, Libertas Mathematica, University of Texas at Arlington, Vol. XIX, 143-154..

[7] F. Smarandache (2002a), A Unifying Field in Logics: Neutrosophic Logic, in Multiple-Valued Logic / An International Journal, Vol. 8, No. 3, 385-438, 2002,

[8] F. Smarandache (2002b), Neutrosophy, A New Branch of Philosophy, in Multiple-Valued Logic / An International Journal, Vol. 8, No. 3, 297-384, 2002.

[9] F. Smarandache (2002c), editor, Proceedings of the First International Conference on Neutrosophy, Neutrosophic Logic, Neutrosophic Set, Neutrosophic Probability and Statistics,University of New Mexico, Gallup Campus, Xiquan, Phoenix, 147 p., 2002,

[10] F. Smarandache (2003), Definition of Neutrosophic Logic – A Generalization of the Intuitionistic Fuzzy Logic, Proceedings of the Third Conference of the European Society for FuzzyLogic and Technology, EUSFLAT 2003, September 10-12, 2003, Zittau, Germany; University of Applied Sciences at Zittau/Goerlitz, 141-146.

[11] Fuzzy Logic Toolbox User's Guide (2009) The MathWorks Inc.

[12]L.A. Zadeh, "The Role of Fuzzy Logic in the Management of Uncertainty in Expert Systems," Fuzzy Sets and Systems, Vol. 11,1983,pp. 197- 227

[13]L.A. Zadeh, "ATheory of Approximate Reasoning," Machine Intelligence, Vol. 9,John Wiley & Sons, New York, 1979, pp.149-194.

[14] L.A. Zadeh, "Outline of a New Approach to the Analysis of Complex Systems and Decision Processes," IEEE Trans. Systems, Man,and Cybernetics, Vol. 3, 1973, pp. 28-44.

[15] L. A. Zadeh, Fuzzy sets, Inf. Control 8 (1965), 338-353.