

**RESEARCH ARTICLE****Handling Uncertainty using Probability Theory, Fuzzy Logic, and Belief Based Systems - A Comparison**

V. Bharath, Akshaj Jain, Sameia Suha, S. R. Rashmi

*Department of Computer Science and Engineering, Dayananda Sagar College of Engineering, Bengaluru, Karnataka, India***Received: 17-04-2018, Revised: 01-05-2018, Accepted: 01-06-2018****ABSTRACT**

There are various ways in which we can handle situations of uncertainty, here, we will see all those ways in which uncertainty can be handled and how the evolution of these processes occurred because of the advantages and disadvantages they offered, we will also see the different types of uncertainties and what actually differentiates these.

**Key words:** Belief rule base, fuzzy logic, probability, uncertainty

**INTRODUCTION**

Uncertainty can be described as situations in which there is ambiguity in decisions or if the information is unknown. It is the state which lacks certainty, and there is not enough knowledge to exactly describe the current state, a future outcome, and more than one state. A doubt in events to occur by chance or randomness, lack of enough knowledge, or by vagueness is known as uncertainty. The Webster dictionary defines it as “Ranges from a mere lack of absolute sureness to such vagueness as to preclude anything more than guesswork.” Thus, uncertainty can mean a whole load of things; thus, it is very important to classify it and define which type of uncertainty we mean when we use the term. Some types of uncertainties are:

- a. Ambiguity is a form of uncertainty which involves more than one outcome, or the outcome does not have a clear meaning. Ambiguity arises in situations where there are different interpretations of the same scenario. Fuzziness is described by ambiguity. For example, two people having a conversation and two people arguing, these two scenarios depend on the interpretation of the analyst.
- b. Vagueness is a form of uncertainty in which we cannot clearly differentiate between different classes. It is something which is not clearly

expressed or stated. It comes because of ambiguity. For example, age of a person, there is no clear classification of young, middle age, and old.

- c. Randomness: Applies to that which occurs or is done without careful choice, aim, and plan. Chance emphasizes accidental occurrence without prearrangement or planning. This occurs purely due to randomness and not because of ambiguity or lack of knowledge. Randomness is a state which does not follow any specific pattern. Since human performs variety of activities in different ways, it is tough to distinguish a particular pattern. For example, arrival of people at the mall is random.
- d. Incompleteness often results in ambiguity; it is a state where essential evidence is missing. For instance, if a cat initiates the process of eating but does not complete the meal. Furthermore, an activity cannot be identified with the high level of confidence when there is inadequate information.

Uncertainty can also be classified in terms of its dimensions. One of the dimensions of uncertainty is severity. Severity depends on the amount of information that is relevant to the decision-making process is available to the agent.

**Levels of severity**

- a. Ignorance: When the agent has no decision-relevant information.

**Address for Corresponding:**

S. R. Rashmi

E-mail: [rashmimugdha@gmail.com](mailto:rashmimugdha@gmail.com)

- b. Severe Uncertainty: When the agents have adequate information to make a partial or imprecise judgment/decision.
- c. Mild Uncertainty: When the agents have sufficient information to make a precise judgment/decision.
- d. Certainty: When the value of the judgment/decision is given or known.

The rest of the paper is divided into different sections where section 2 contains information about Probability theory, section 3 about fuzzy logic (FL), section 4 about belief-based systems, and section 5 is about the comparisons in the systems.

## PROBABILITY THEORY

If a probability theory is applied to a given reasoning system, then we take/assume a sample space  $Q$ , where  $Q$  has all the propositions the given reasoning system can have, the propositions are generated from basic propositions and using the logical operators OR, AND, and NOT. Then, a probability distribution  $P$  is defined on  $Q$  where for  $x$  belonging to  $Q$ ,  $P(x)$  is in the range  $[0,1]$ . The function  $P$  should also satisfy:

- $P(x \vee x) = 1$ .
- $P(x \vee y) = P(x) + P(y)$  if  $y \in S$  and  $x \wedge y$  is false.<sup>[1]</sup>

There are two major disadvantages of the probability theory, they are:

- The uncertain event must be in the sample space  $Q$ .
- The probability of the event must be  $>0$ , and the proposition must be binary.

To help with some of the disadvantages, people started using FL and evidential reasoning (ER).

## FL/FUZZY RULE BASED EXPERT SYSTEMS

FL is a form of many-valued logic in which the truth values of variables may be any real number between 0 and 1. It is employed to handle the concept of partial truth, where the truth value may range between completely true and completely false. FL is a method of reasoning that resembles human reasoning. The approach of FL imitates the way of decision-making in humans that involve all intermediate possibilities between digital values YES and NO.

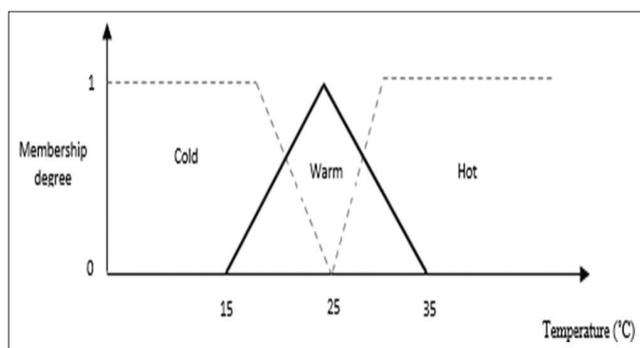
The conventional logic block that a computer can understand takes precise input and produces a definite output as TRUE or FALSE, which is equivalent to human's YES or NO.

FL maps the inputs between  $[0..1]$ , unlike probability theory that is associated with either true or false. FL technology has the capability of reasoning like human. FL consists of process of fuzzification, FL operators, if then rules and defuzzification. The initialization steps of FL include defining the linguistic terms, membership functions and constructing the rule base. Using these membership functions, the crisp inputs are converted into fuzzy values; this process is called as fuzzification. The inference engine evaluates the fuzzy rules and combines the result of the rules. The defuzzification process converts the fuzzy output data into crisp data. The membership functions are used in the process of fuzzification and defuzzification.<sup>[2]</sup>

FL handles vagueness which is a form of uncertainty. This form of uncertainty is handled by assigning a required degree of membership function for the fuzzy variables. For example, if the temperature is considered as a fuzzy variable then cold, warm, and hot are the linguistic terms that can be assigned to temperature with the membership degree as shown in Figure 1.

Fuzzy rules are simple if-then rules with antecedent and consequent part. Antecedent part consists of a condition and consequent part consists of a conclusion. For example, if (temperature is hot) then turn on AC.

There are various works on FL and fuzzy expert systems for decision-making, medical diagnosis, and action recognition but are not limited to them. In medical diagnosis systems, uncertainty is captured when patients are not capable of describing their problem precisely to the doctor. Amrollahi *et al.*<sup>[3]</sup> proposed a neuro-fuzzy classification approach that uses fuzzy rules to diagnose thyroid disease. FL is used to handle the imprecise knowledge encountered during the decision-making process. A similar approach was used to diagnose multiple sclerosis considering uncertainty in symptoms and clinical observations.<sup>[4]</sup> A prominent work on traffic monitoring system using FL was carried out in Waingankar and Kulkarni<sup>[5]</sup> where the FL controller decides on extensions based on arrival and queuing of vehicles. An adaptive traffic light system was proposed considering the



**Figure 1:** Fuzzy representation describing temperature range

fact that the vehicles arriving at the junction are inconsistent.<sup>[6]</sup> The traffic light is controlled based on a FL controller.

Although FL can address uncertainty due to linguistic terms such as vagueness, it fails to handle uncertainty such as incompleteness and ignorance. Hence, to also represent other types of uncertainty belief rule-based expert systems have been developed.

## ER/BELIEF RULE-BASED EXPERT SYSTEMS

The ER approach is a generic evidence-based multi-criteria decision analysis (MCDA) approach for dealing with problems having both quantitative and qualitative criteria under various uncertainties including ignorance and randomness. It has been used to support various decision analysis, assessment, and evaluation activities such as environmental impact assessment and organizational self-assessment based on a range of the quality model.

A belief structure is a distributed assessment with beliefs. It is used in the ER approach for MCDA to represent the performance of an alternative option on a criterion.

The use of belief decision matrices for MCDA problem modeling in the ER approach results in the following features:

- An assessment of an option can be more reliably and realistically represented by a belief decision matrix than by a conventional decision matrix.
- It accepts data of different formats with various types of uncertainties as inputs, such as single numerical values, probability distributions, and subjective judgments with belief degrees.

- It allows all available information embedded in different data formats, including qualitative and incomplete data, to be maximally incorporated in assessment and decision-making processes.

- It allows assessment outcomes to be represented more informatively.

In belief rules, each antecedent attribute consists of referential value, and each consequent attribute has a degree of belief. Ignorance is handled by finding the summation of the belief degree. If the sum is equal to 1 then it can be said that there is no ignorance and if it is  $<1$  then some ignorance exists. Belief rules are written as shown below.

IF ( $S_{k1}$  is  $A_1^k$ ) and ( $S_{k2}$  is  $A_2^k$ )... and ( $S_{kN}$  is  $A_N^k$ )

Then  $\{(D_1 \text{ is } \beta_{1k}), (D_2 \text{ is } \beta_{2k}) \dots (D_T \text{ is } \beta_{Tk})\}$

Where  $A_1^k, A_2^k \dots A_N^k$  are the referential values and  $\beta_{1k}, \beta_{2k} \dots \beta_{Tk}$  are the belief degrees.

The inference part of the belief rule-based expert system consists input transformation, rule activation weight calculation, belief update, and rule aggregation; this is called the RIMER approach which consists of ER algorithm.<sup>[7]</sup>

In the field of medical diagnosis, belief rule-based expert system has made its way by handling uncertainty such as randomness, ignorance, and incompleteness, for example, for the diagnosis of an asthma cough can be a symptom that is ignored by the patient, hence, the initial belief degree consists of ignorance or incompleteness.<sup>[8]</sup> A belief rule-based framework to support clinical decisions under uncertainty using ER was proposed in Islam *et al.*<sup>[9]</sup> A similar work was done on a decision support system to measure heart failure<sup>[10]</sup> and acute coronary<sup>[11]</sup> suspicion from symptoms and risk factors. Another belief rule-based expert system to control traffic system was proposed. Traffic congestion occurs due to various factors such as number of vehicles and road size which involves uncertainty.<sup>[12]</sup> A system to predict power usage effectiveness of the data centers under uncertainty was developed and compared with genetic algorithms.<sup>[13]</sup>

## COMPARISONS

ER mostly builds on the evidence and also uses qualitative criteria for making decisions whereas the probability theory only uses quantitative approaches, it can deal with ignorance. Thus, ER can actually have real-life usage whereas

**Table 1. Comparison of different ways to handle uncertainty**

Name	Advantages	Disadvantages
Probability Theory	Not much computation required	Very little practical use in decision-making
ER	Can handle ignorance	Less use in decision-making than FL
FL	Most useful for real-life decision-making	Does not necessarily provide a definitive answer to the question

ER: , FL:

the probability theory has very little to no use in real life decision-making scenarios. Table 1 gives the comparison of different ways to handle uncertainty.

FL and probability address different forms of uncertainty. While both FL and probability theory can represent degrees of certain kinds of subjective belief, fuzzy set theory uses the concept of fuzzy set membership; the concept of fuzzy sets was developed in the mid-twentieth century as a response to the lacking of probability theory for jointly modeling uncertainty and vagueness. An interesting example of fuzzy sets can include cold, warm and hot, when the cold is about 0.2 then, the warmth reaches 0.8 or so, and hot is 0 when the cold is 0, then the hotness starts increasing. Thus, FL provides us with much more choices in decision-making and can also handle vagueness and multiple avenues.

## REFERENCES

1. Wang P. The limitation of bayesianism. *Artif Intell* 2004;158:97-106.
2. Fuzzy Logic examples. *Artificial Intelligence Course: Module 9: Fuzzy logic-Tutorial*; 2016.
3. Biyouki SA, Zarandi MF. Fuzzy Rule-based Expert System for Diagnosis of Thyroid Disease. In 2015 IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB); 2015.
4. Ghahazi MA, Zarandi MH, Damiechi-Darasi SR, Harirchian MH. Fuzzy Rule Based Expert System for Diagnosis of Multiple Sclerosis. Boston, MA, USA: IEEE Conference; 2014.
5. Waingankar PG, Kulkarni GH. Fuzzy Logic Based Traffic Light Controller. In *Second International Conference on Industrial and Information Systems*. Sri Lanka: ICIS; 2007.
6. Wahab M, Yaakop M, Salam AA, Zaharudin Z, Adam I. Adaptive Fuzzy Logic Traffic Light Management System. Malaysia: 4<sup>th</sup> International Conference on Engineering Technology and Technopreneuship (ICE2T); 2014.
7. Yang JB, Liu J, Sii HS, Wang HW, Wang J. Belief rule-base inference methodology using the evidential reasoning approach-rimer. *IEEE Trans Syst Man Cybern* 2006;36:266-85.
8. Hossain E, Khalid S, Haque MA, Hossain MS. A Belief Rule-Based (BRB) Decision Support System for Assessing Clinical Asthma Suspicion. Norway: Scandinavian Conference on Health Informatics; 2014.
9. Islam MM, Hossain MS, Rahaman S. A Belief Rule Based Clinical Decision Support System Framework. Dhaka, Bangladesh: 17<sup>th</sup> International Conference on Computer and Information Technology (ICCIT); 2014.
10. Rahaman S, Hossain MS. A Belief Rule Based Clinical Decision Support System to Assess Suspicion of Heart Failure from Signs, Symptoms And Risk Factors. Dhaka, Bangladesh: 2013 International Conference on Informatics, Electronics and Vision (ICIEV); 2013. p. 2013.
11. Rahaman S, Mustafa R, Andersson K, Hossain MS. A belief rule-based expert system to assess suspicion of acute coronary syndrome (ACS) under uncertainty. *Soft Comput* 2017;2017:1-16.
12. Sinha H, Mustafa R, Hossain AM. A Belief Rule Based Expert System to Control Traffic Signals under Uncertainty. Bangladesh: 1<sup>st</sup> International Conference on Computer and Information Engineering; 2015.
13. Rahaman S, Kor AL, Andersson K, Pattinson C, Hossain MS. A belief rule based expert system for datacenter PUE prediction under uncertainty. *IEEE Trans Sustain Comput* 2017;2:140-53.