Dealing with Uncertainty in Expert Systems

Sonal Dubey, R. K. Pandey, S. S. Gautam

Abstract*: *The aim of artificial intelligence is to develop tools for representing piece of knowledge and providing inference mechanism for elaborating conclusion of knowledge from stored information. The available knowledge is far from being certain, precise and complete. In Expert systems the word uncertainty is related to the working with inexact data, imprecise information, handling identical situation, reliability of the results etc. An expert system allows the user to assign probabilities, certainty factors, or confidence levels and many more techniques to any or all input data. This feature closely represents how most problems are handled in the real world. An expert system can take all relevant factors into account and make a recommendation based on the best possible solution rather than the only exact solution to handle such problems. This paper describes the various types of uncertainty, its sources and different approaches to handle uncertainty.

Index Terms:* certainty factor, *expert system, fuzzy logic, soft computing uncertainty management.

I. INTRODUCTION

In Expert systems the word uncertainty is related to the working with inexact data, imprecise information, handling identical situation, reliability of the results etc. An expert system allows the user to assign probabilities, certainty factors, or confidence levels and many more techniques to any or all input data. This feature closely represents how most problems are handled in the real world. An expert system can take all relevant factors into account and make a recommendation based on the best possible solution rather than the only exact solution to handle such problems. Uncertainty is defined as the lack of the exact knowledge that would enable us to reach a perfectly reliable conclusion. [Anuradha et al; 2013]. Classical logic permits only exact reasoning. It assumes that perfect knowledge always exists and the law of the excluded middle can always be applied. The general term uncertainty describes any element of the model that cannot be asserted with complete confidence. Within this general condition, there are several distinct types of uncertainty [Negnevitsky Michael, 2005].

II. TYES OF UNCERTAINTY

a) **Uncertainty-**it is not possible to determine whether an assertion in the model is true or false. For example, there might be uncertainty about the fact "the height of plant is 38."

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b) **Imprecision-**the information available in the model is not as specific as it should be. For example, when a distinct value is required, the information available might be a range (e.g., "the height of plant is between 37 and 43"**)**, disjunctive (e.g., "the height of plant is either 37 or 43"), negative (e.g., " height of plant is not 37"), or even unknown (often referred to as incompleteness).

c) **Vagueness-**the model includes elements (e.g., predicates or quantifiers) that are inherently vague; for example, "Plant is in early middle age." A particular formalization of vagueness is based on the concept of fuzziness.

d) **Inconsistency--**the model contains two or more assertions that cannot be true at the same time; for example, “height of plant is between 37 and 43" and "the height of plant is 35."

e) **Ambiguity--**some elements of the model lack complete semantics, leading to several possible interpretations. For example, it may not be clear whether stated temperature is in Fahrenheit or Celsius.

III. SOURCES OF UNCERTAINTY

- Information can be unreliable: This is usually due either to ill-defined domain concepts or to inaccurate data. In addition. Rule-based systems often suffer from weak implications when the expert is unable to establish a concrete correlation between a rule’s premise and its conclusion. Many, such systems treat weak implications by quantifying the degree of correlation: for example. MYCIN introduced numeric certainty factors (CF) for expressing correlation\. and the resultant rules took the form

  “If <premise> Then (CF) <conclusion>.” l
- Descriptive (or implementation) languages lack precision: The numerous ambiguities in natural language are rarely clarified during translation to a formal language. As a result, rules that are not expressed precisely in the formal language can be misinterpreted. Thus. A perfect matching of facts with premises will rarely be adequate: the meaning of the facts must be approximately matched with those of the premises.
- Inferences are sometimes drawn with incomplete information: When the available information is incomplete. Rule-based representations can‘t hope to be an) better. The remedy resembles that for imprecision approximate pattern matching - except that the system accepts the value “unknown” while evaluating the premise’s degree of certainty.

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- Experts sometimes disagree: Combining the views of multiple experts into a consensus knowledge base is difficult, confusing, and frequently impossible. When all experts draw similar conclusions, consensus is generally derivable. When the experts have contradictory viewpoints, however, the combined conclusions are suspect. A rule-based system must resolve all conflicting rules before it can develop a consensus knowledge base.
- Imprecise language. Our natural language is inherently ambiguous and imprecise. We describe facts with such terms as often and sometimes, frequently and hardly ever. As a result, it can be difficult to express knowledge in the precise IF-THEN form of production rules. However, if the meaning of the facts is quantified, it can be used in expert systems. In 1944, Ray Simpson asked 355 high school and college students to place 20 terms like often on a scale between 1 and 100 (Simpson, 1944). In 1968, Milton Hakel repeated this experiment (Hakel, 1968). Their results are presented in Table 1.

Table 1. Quantification of Ambiguous and Imprecise Terms on a Time-Frequency Scale

Ray Simpson (1944)		Milton Hakel (1968)	
Term	Mean value	Term	Mean value
Always	99	Always	100
Very often	88	Very often	87
Usually	85	Usually	79
Often	78	Often	74
Generally	78	Rather often	74
Frequently	73	Frequently	72
Rather often	65	Generally	72
About as often as not	50	About as often as not	50
Now and then	20	Now and then	34
Sometimes	20	Sometimes	29
Occasionally	20	Occasionally	28
Once in a while	15	Once in a while	22
Not often	13	Not often	16
Usually not	10	Usually not	16
Seldom	10	Seldom	9
Hardly ever	7	Hardly ever	8
Very seldom	6	Very seldom	7
Rarely	5	Rarely	5
Almost never	3	Almost never	2
Never	0	Never	0

IV. REPRESENTATION OF UNCERTAINTY

The three basic methods of representing uncertainty are numeric, graphical, and symbolic.

Numeric Representation of Uncertainty

The most common method of representing uncertainty is numeric, using a scale with two extreme numbers. For example, 0 can be used to represent complete uncertainty, and 1 or 100 can represent complete certainty. Although such representation seems trivial to some people (maybe because it is similar to the representation of probabilities), it is very difficult for others. In addition to the difficulties of using numbers, there are problems with cognitive bias. For example, experts figure the numbers based on their own experience and are influenced by their own perceptions. Finally, people may inconsistently provide different numeric values at different times.

Graphical Representation of Uncertainty

Although many experts are able to describe uncertainty in terms of numbers, such as “It is 85 percent certain that,” some find this difficult. The use of horizontal bars may help experts to express their confidence in certain events. Such a bar is shown in Figure 1. Experts are asked to place markers somewhere on the scale. Thus, in Figure 1, Expert A expresses very little confidence in the likelihood of inflation, whereas Expert B is more confident that inflation is coming. Even though some experts prefer graphical presentation, graphs are not as accurate as numbers. Another problem is that most experts do not have experience in marking graphical scales (or setting numbers on the scale). Many experts, especially managers, prefer ranking (which is symbolic) over either graphical or numeric methods.

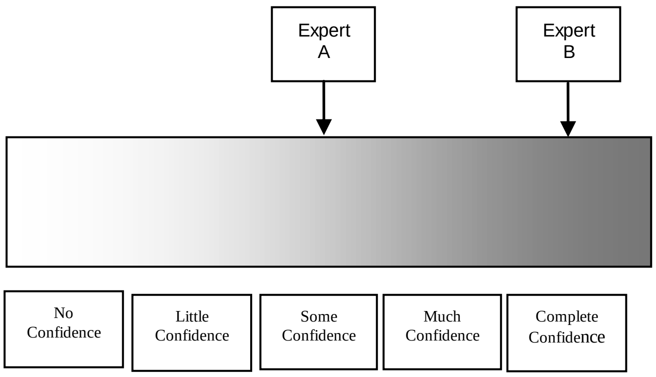

Figure 1. Confidence Scale about Inflation

Symbolic Representation of Uncertainty

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There are several ways to represent uncertainty by using symbols. For example, an expert may be asked to assess the likelihood of inflation on a five-point scale:
very unlikely, unlikely, neutral, likely, and very likely. Ranking is a very popular approach among experts who have non quantitative preferences. Ranking can be either ordinal (i.e., listing of items in order of importance) or cardinal (i.e., ranking complemented by numeric values). Symbolic representation methods are often combined with numbers or converted to
numeric values.

V. UNCERTAINTY MANAGEMENT

It is very easy to derive decisions for the problems which are precisely defined and all the specific information is given or the knowledge is represented with certainty. Various quantitative and qualitative methods have been developed to handle uncertain or imprecise information in an expert system as shown in Figure 2. Quantitative methods may be classified into one valued approach based on probability theory, Bayes' rules and confirmation theory, two-valued approach based on Dempster-Shafer theory, and set-valued approach based on fuzzy set theory, incidence calculus and rough set theory. Qualitative methods include modal logics, non monotonicity, plausible reasoning and theory of endorsements. Obviously, no single method can handle uncertainty perfectly. The basis for the selection depends on the nature of uncertainty. Some of the approaches to deal with uncertainty are:

The Probability Ratio

The degree of confidence in a premise or a conclusion can be expressed as a probability. Probability is the chance that a particular event will occur (or not occur). It is a ratio computed as follows: The probability of X occurring, stated as P(X), is the ratio of the number of times X occurs, N(X), to the total number of events that take place. Multiple probability values occur in many systems. For example, a rule can have an antecedent with three parts, each with a probability value. The overall probability of the rule can be computed as the product of the individual probabilities if the parts of the antecedent are independent of one another. In a three-part antecedent, the probabilities may be .9, .7, and .65, and the overall probability is figured like this:

$$P = (.9)(.7)(.65) = .4095$$

The combined probability is about 41 percent. But this is true only if the individual parts of the antecedent do not affect or interrelate with one another. Sometimes one rule references another. In this case, the individual rule probabilities can propagate from one to another, so evaluate the total probability of a sequence of rules or a path through the search tree to determine whether a specific rule fires. Or use of the combined probabilities to predict the best path through the search tree is done. In knowledge-based systems, there are several methods for combining probabilities. For example, they can be multiplied (i.e., joint probabilities) or averaged (using a simple or a weighted average); in other instances, only the highest or lowest values are considered. In all such cases, rules and events are considered independent of each other. If there are dependencies in the system, the Bayesian extension theorem can be used.

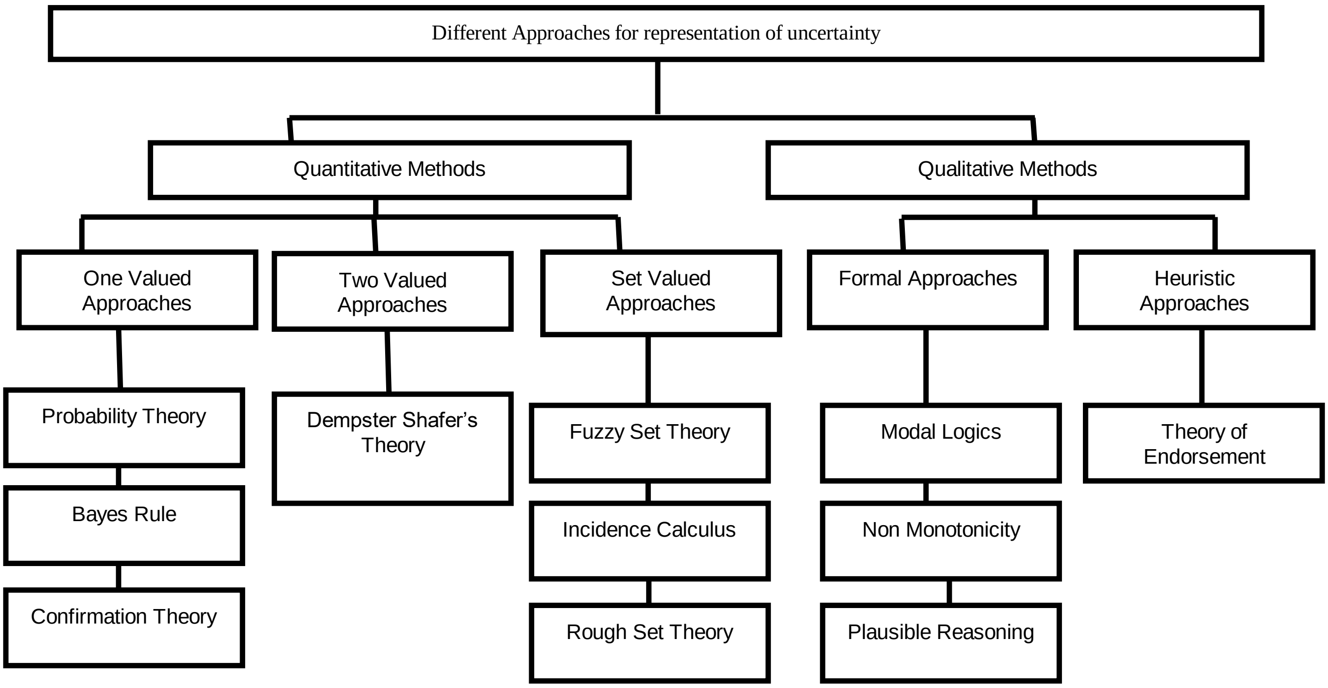


Figure 2: Different Approaches for Representation of Uncertainty

The Bayesian Approach

Bayes's theorem is a mechanism for combining new and existent evidence, usually given as subjective probabilities. It is used to revise existing prior probabilities based on new information. The Bayesian approach is based on subjective probabilities (i.e., probabilities estimated by a manager without the benefit of a formal model); a subjective probability is provided for each proposition. If E is the evidence (i.e., the sum of all information available to the system), then each proposition, P, has associated with it a value representing the probability that P holds in light of all the evidence, E, derived by using Bayesian inference. Bayes's theorem provides a way of computing the probability of a particular event, given some set of observations that have already been made. The main point here is not how this value is derived but that what we know or infer about a proposition is represented by a single value for its likelihood. This approach has two major deficiencies. The first is that the single value does not tell us much about its precision, which may be very low when the value is derived from uncertain evidence. Saying that the probability of a proposition being true in a given situation is .5 (in the range 0–1) usually refers to an average figure that is true within a given range. For example, .5 plus or minus .001 is completely different from .5 plus or minus .3, yet both can be reported as .5.The second deficiency is that the single value combines the evidence for and against a proposition, without indicating the individual value of each. The subjective probability expresses the degree of belief, or how strongly a value or a situation is believed to be true. The Bayesian approach, with or without new evidence, can be diagrammed as a network. Probability theory is the oldest and best-established technique to deal with inexact knowledge and random data. It works well in such areas as forecasting and planning, where statistical data is usually available and accurate probability statements can be made. However, in many areas of possible applications of expert systems, reliable statistical information is not available or we cannot assume the conditional independence of evidence. As a result, many researchers have found the Bayesian method unsuitable for their work. This dissatisfaction motivated the development of the certainty factors theory.

The Dempster–Shafer Theory of Evidence

The Dempster–Shafer theory of evidence is a well-known procedure for reasoning with uncertainty in artificial intelligence. It can be considered an extension of the Bayesian approach. The Dempster–Shafer approach distinguishes between uncertainty and ignorance by creating belief functions. Belief functions allow us to use our knowledge to bound the assignment of probabilities when the boundaries are unavailable. The Dempster–Shafer approach is especially appropriate for combining expert opinions because experts differ in their opinions with a certain degree of ignorance and, in many situations, at least some epistemic information (i.e., information constructed from vague perceptions).The Dempster–Shafer theory can be used to handle epistemic information as well as ignorance or lack of information. Unfortunately, it assumes that the sources of information to be combined are statistically independent of each other. In reality, there are many situations in which the knowledge of experts overlaps (i.e., there are dependencies among sources of information). The Dempster-Shafer approach enables ignorance to be expressed explicitly and does not narrowly restrict belief in hypothesis negation once belief in its occurrence is known. These strong points leads to combinatorial explosion because the hypothesis space is the power set of all the possible hypothesis. To fill the huge gap the human expert has to give all the basic probabilities assignments for the interesting subsets only. [Ng Keung Chi and Abramson Bruce, 1990] The DST does not provide any guidance on how these assignments should be obtained. And there is no effective procedure for drawing inferences from belief functions. Hence it is not surprising that no expert system has been built using DST.

Certainty Factors and Beliefs

Standard statistical methods are based on the assumption that an uncertainty is the probability that an event (or fact) is true or false. Certainty theory is a framework for representing and working with degrees of belief of true and false in knowledge-based systems. In certainty theory as in fuzzy logic, uncertainty is represented as a degree of belief. There are two steps in using every nonprobabilistic method of uncertainty. First, it is necessary to be able to express the degree of belief. Second, it is necessary to manipulate (e.g., combine) degrees of belief when using knowledge-based systems. Certainty theory relies on the use of certainty factors. Certainty factors (CF) express belief in an event (or a fact or a hypothesis) based on evidence (or on the expert's assessment). There are several methods of using certainty factors to handle uncertainty in knowledge-based systems. One way is to use 1.0 or 100 for absolute truth (i.e., complete confidence) and 0 for certain falsehood. Certainty factors are not probabilities. For example, when we say there is a 90 percent chance of rain, there is either rain (90 percent) or no rain (10 percent). In a non probabilistic approach, we can say that a certainty factor of 90 for rain means that it is very likely to rain. It does not necessarily mean that we express any opinion about our argument of no rain (which is not necessarily 10).Thus, certainty factors do not have to sum up to 100. Certainty theory introduces the concepts of belief and disbelief (i.e., the degree of belief that something is not going to happen).These concepts are independent of each other and so cannot be combined in the same way as probabilities, but they can be combined according to the following formula:

CF(P,E) = MB(P,E) 2 MD(P,E)

Where: CF = certainty factor

MB = measure of belief

MD = measure of disbelief

P = probability

E = evidence or event

Another assumption of certainty theory is that the knowledge content of rules is much more important than the algebra of confidences that holds the system together. Confidence measures correspond to the information evaluations that human experts attach to their conclusions (e.g., “It is probably true” or “It is highly unlikely”). Certainty factors represent information about how certain the conclusion in a rule may be. Certainty factors can be attached both to the conditions in an if-then rule and to its conclusion. They are ad hoc values, given by the experts based on experience or by the users when providing initial data. Certainty factors are not probabilities, they represent beliefs about how strong a given evidence is, to what degree the evidence supports a hypothesis. Certainty factors are measured using various scales bot numeric (0 – 100, 0 – 10, 0 – 1, -1 to- 1) and linguistics ones (certain, fairly certain, likely, unlikely, highly unlikely, definitely not).

- Higher certainty factors indicate strong confidence in a hypothesis.
- Certainty factors that approach -1 indicate confidence against a hypothesis.
- Certainty factors around 0 mean that we don’t have information either for or against a hypothesis.

Table 2. Uncertain Terms and their Interpretation [Negnevitsky Michael, 2005]

Term	Certainty Factor
Definitely not	-1:0
Almost certainly not	-0:8
Probably not	-0:6
Maybe not	-0:4
Unknown	-0:2 to +0:2
Maybe	+0.4
Probably	+0.6
Almost certainly	+0.8
Definitely	+1.0

As the certainty factor (CF) approaches 1, the evidence is stronger for a hypothesis; as CF approaches - 1, the confidence against the hypothesis gets stronger; and a CF around 0 indicates that either little evidence in the rule's reliability. Certainty measures may be adjusted to tune the system's performance, although slight variations in the confidence measure tend to have little effect on the overall of the system. This second role of certainty measures confirms the belief that "the knowledge gives the power", than is, the integrity of the knowledge itself best supports the production of correct diagnoses [Rasal Isram , Wicaksana I Wayan Simri, 2013]. The premises for each rule are formed of 'and's and 'or's of a number of facts. When a production rule is used, the certainty factors associated with each condition of the premise are combined to produce a certainty measure for the overall premise as follows:

For P1 and P2, premises of the rule,

CF(P1 and P2) = MIN(CF(P1), CF(P2)) -----(1)

CF(P1 or P2) = MAX(CF(P1), CF(P2))---------(2)

The combined CF of the premises, using the above rules, is then multiplied by the CF of the rule itself to get the CF for the conclusion of the rule. In expert systems with certainty factors, the knowledge base consists of a set of rules that have the following syntax:

IF <evidence> THEN <hypothesis> {cf}

where cf represents belief in hypothesis H given that evidence E has occurred. The certainty factors theory is based on two functions: measure of belief MB (H,E) and measure of disbelief MD(H,E). Certainty factors are used if the probabilities are not known or cannot be easily obtained. Certainty theory can manage incrementally acquired evidence, the conjunction and disjunction of hypotheses, as well as evidences with different degrees of belief. Although the certainty factors approach lacks the mathematical correctness of the probability theory, it outperforms subjective Bayesian reasoning in such areas as diagnostics. Certainty factors are used in cases where the probabilities are not known or are too difficult or expensive to obtain. The evidential reasoning mechanism can manage incrementally acquired evidence, the conjunction and disjunction of hypotheses, as well as evidences with different degrees of belief. The certainty factors approach also provides better explanations of the control flow through a rule-based expert system.

Soft Computing

Soft Computing (SC) represents a significant paradigm shift in the aims of computing, which reflects the fact that the human mind, unlike present day computers, possesses a remarkable ability to store and process information which is pervasively imprecise, uncertain and lacking in categoricity. Soft computing is tolerant of imprecision, uncertainty, partial truth, and approximation. In effect, the role model for soft computing is the human mind. The guiding principle of soft computing is: Exploit the tolerance for imprecision, uncertainty, partial truth, and approximation to achieve tractability, robustness and low solution cost and solve the fundamental problem associated with the current technological development: the lack of the required intelligence of the recent information technology that enables human-centered functionality. The basic ideas underlying soft computing in its current incarnation have links to many earlier influences, among them Zadeh’s 1965 paper on fuzzy sets; the 1975 paper on the analysis of complex systems and decision processes; and the 1979 report (1981 paper) on possibility theory and soft data analysis. [Ramík Jaroslav 2001]The inclusion of neural computing and genetic computing in soft computing came at a later point. The principal constituents of Soft Computing (SC) are:

- Fuzzy Systems (FS), including Fuzzy Logic (FL);
- Evolutionary Computation (EC), including Genetic Algorithms (GA);
- Neural Networks (NN), including Neural

Computing (NC);
- Machine Learning (ML);
- Probabilistic Reasoning (PR)

(1)

Table 3. Comparison of Uncertainty Models And Approaches [Liang Yeow Wei and Mahmud, Rohana 2012]

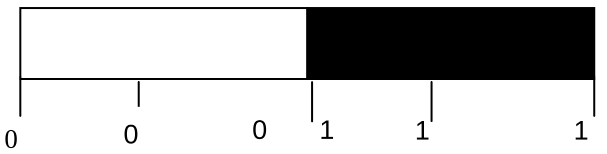
Model/Approach	Method to Elicit Uncertainty Value	Target Area/Problem Solving
Classical Probability	Purely based on mathematical probability. Prediction of *a posteriori* events are based on prior probability provided byexperts.	Prediction of *a posteriori* event
Bayesian Theory	Using mathematical probability to predict prior evidence based on *a posteriori* evidence. Experts should provide the past data.	Prediction of evidence or event in an inference network. Nearly universal in application.
Certainty-factor	Values obtained from expert's subjective interpretation. Involve user past experience in determining values.Values can be interpreted and classified by the uncertainty terms. The overall certainty-factor value isthe product of all the premises in the rules.	Used to judge uncertain evidence or conclusion. Deals with evidence in terms of their belief or disbelief of each hypothesis
Fuzzy Logic	Values obtained from user interpretation and experimentation. User defined linguistic variables and fuzzy sets, based on past experience or experiments	Deals with imprecise and vague information or fuzzy quantifiers

Fuzzy Logic

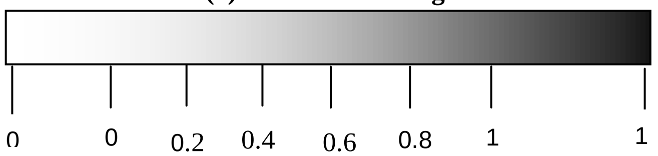
Fuzziness is a way to represent uncertainty, possibility and approximation. If something is fuzzy, it means that we are unable to define precisely its boundaries. Fuzzy logic is a good tool for situations where uncertainty is somewhat intrinsic to the system. This uncertainty can appear in a variety of ways.

1) Fuzzy, or multi-valued logic was introduced in the 1930s by Jan Lukasiewicz, a Polish logician and philosopher . He studied the mathematical representation of fuzziness based on such terms as tall, old and hot. While classical logic operates with only two values 1 (true) and 0 (false), Lukasiewicz introduced logic that extended the range of truth values to all real numbers in the interval between 0 and 1. He used a number in this interval to represent the possibility that a given statement was true or false. For example, the possibility that a man 181cm tall is really tall might be set to a value of 0.86. It is likely that the man is tall. This work led to an inexact reasoning technique often called possibility theory.
2) Later, in 1937, Max Black, a philosopher, published a paper called 'Vagueness: an exercise in logical analysis'. In this paper, he argued that a continuum implies degrees. Imagine, he said, a line of countless 'chairs'. At one end is a Chippendale. Next to it is a near-Chippendale, in fact indistinguishable from the first item. Succeeding 'chairs' are less and less chair-like, until the line ends with a log. When does a chair become a log? The concept chair does not permit us to draw a clear line distinguishing chair from not-chair. Max Black also stated that if a continuum is discrete, a number can be allocated to each element. This number will indicate a degree. But the question is degree of what. Black used the number to show the percentage of people who would call an element in a line of 'chairs' a chair; in other words, he accepted vagueness as a matter of probability. However, Black's most important contribution was in the paper's appendix. Here he defined the first simple fuzzy set and outlined the basic ideas of fuzzy set operations.
3) In 1965 Lotfi Zadeh, Professor and Head of the Electrical Engineering Department at the University of California at Berkeley, published his famous paper 'Fuzzy sets'. In fact, Zadeh rediscovered fuzziness, identified and explored it, and promoted and fought for it [Negnevitsky Michael 2005]. Zadeh extended the work on possibility theory into a formal system of mathematical logic, and even more importantly, he introduced a new concept for applying natural language terms. This new logic for representing and manipulating fuzzy terms was called fuzzy logic, and Zadeh became the Master of fuzzy logic.
4) There are two assumptions that are fundamental for the use of formal set theory. The first is with respect to set membership; \for any element and a set belonging to some universe, the element is either a member of the set or else it is a member of the complement of the set". The second assumption, referred to as the law of excluded middle, states that an " element cannot belong to both a set and also a complement". These two fundamental assumptions for formal set theory are contravened in Lotfi Zadeh's fuzzy set theory .
5) Unlike two-valued Boolean logic, fuzzy logic is multi-valued. It deals with degrees of membership and degrees of truth. Fuzzy logic uses the continuum of logical values between 0 (completely false) and 1 (completely true). Instead of

just black and white, it employs the spectrum of colours, accepting that things can be partly true and partly false at the same time. As can be seen in Figure 2, fuzzy logic adds a range of logical values to Boolean logic. Classical binary logic now can be considered as a special case of multi-valued fuzzy logic.



(a) Boolean Logic



(b) Multivalued Logic

Figure 3. Range of Logical Values in Boolean and Fuzzy Logic: (a) Boolean Logic; (b) Multivalued Logic

Crisp set theory is governed by a logic that uses one of only two values: true or false. This logic cannot represent vague concepts, and therefore fails to give the answers on the paradoxes. The basic idea of the fuzzy set theory is that an element belongs to a fuzzy set with a certain degree of membership. Thus, a proposition is not either true or false, but may be partly true (or partly false) to any degree. This degree is usually taken as a real number in the interval [0,1].

VI. CONCLUSION

In short many approaches to handle uncertainty in expert systems were discussed in this paper. All the approaches have their weakness and strength. We cannot say that an approach is ideal for any expert systems. It all depends upon the problem to be solved. In my work "Multimedia fuzzy based diagnostic expert system for pest management in chickpea" fuzzy logic and certainty factor has been used to handle vagueness in the expert system developed.

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