Approaches for Managing Uncertainty in Learning Management Systems

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Abstract

The notion of uncertainty in expert systems is dealing with vague data, incomplete information, and imprecise knowledge. Different uncertainty types which are imprecision, vagueness, ambiguity, and inconsistence need different handling models. Uncertain knowledge representation and analysis is an essential issue. Classical probability, Bayes theory, Dempster–Shafer theory, certainty factor and fuzzy set approaches presented in expert systemsfor managing uncertainty data, but these models are not enough to express uncertain problems. This review paper suggests the multi-valued logic models which are type 2 fuzzy set; intuitionistic fuzzy set; vague set; and neutrosophic set for handling uncertainty in expert systems to derive decisions. The paper presents definitions, basic properties, and differences of these multi-valued logic models. Finally, the study analyzes the relationships between them and provides insights for the application of these models in expert systems for evaluating learning management systems.

Keywords: *Uncertainty; Expert System; Type2 Fuzzy Set; Intuitionistic Fuzzy Set; Vague Set; Neutrosophic Set, Learning Management Systems*

1. Introduction

Uncertainty is the shortage of precise knowledge, incomplete information, and uncertain data, all of which describe the state of the environment regardless of what is the cause of this insufficient data [1]. One of the key problems of artificial intelligence is modeling uncertainty for solving real life problems [2]. Different models have been proposed to deal with uncertainty for solving real life problems by simulating the process of normal human reasoning [3]. Previous studies present Bayes theory, Dempster–Shafer theory, certainty factor and fuzzy logic for dealing with uncertainty in expert systems, but these models are not enough to express uncertainty inproblems [4]. Decision making involves grey areas where it is not true or false; therefore it needs multivalued models to increase understanding of the cognitive outcome better than crisp [5].

Managing uncertainties is a goal for decision makers. They need to identify, classify, characterize, assess and quantify uncertainties data types [3]. This leads to emerging new approaches such as type2 fuzzy, intuitionistic fuzzy, vague and neutrosophic models, all of which give better attribute interpretations [6]. The fuzzy theory was introduced by Professor Lotfi Zadeh in 1965. This theory considers the degree of the membership of elements in a set [7]. Zadeh also introduced type2 fuzzy theory in 1975, in which membership grades themselves are fuzzy [8]. In 1983, Intuitionistic fuzzy set theory presented by Attanssov as an extension of the standard fuzzy sets [9]. The vague set was first proposed by Gau and Buehrer in 1993. It depends on the concept of the degree of membership for truth and the complement of false are not the same [10]. Smarandache in 1999 [11] proposed a new approach called neutrosophic logic, which is able to handle indeterminacy of information which expresses the percentage of unknown parameters.

The expert is a dependable resource of information in fields that lacks data [1]. Expert system simulates human expert thinking to solve problem and take decision in particular domain [12]. It also can be designed for various activities; such as diagnosis, repair, decision support, design and planning, monitoring and control, or instruction and evaluation [13]. Expert system aims to represent types of uncertainties to draw conclusion with the same level of accuracy as would a human expert do [12]. There are four essential types of uncertainties that can arise. They include vagueness: when information is naturally graded, imprecision: when the available information is not specific, ambiguity: when information leads to several possible interpretations, and inconsistency: when two or more information cannot be true at the same time [14][15]. The uncertain problems need imprecise models that could deal with different types of uncertainties to increase the understanding of the outcome [16].

This paper discusses multivalued logic models including type2 fuzzy set theory, intuitionistic fuzzy set, vague set theory, and neutrosophic set theory for managing uncertainty in expert systems. The paper is organized into the following sections: Section 1 provides an introduction to the paper; Section 2 discusses multivalued logic models for managing uncertainty in expert systems; Then Section 3 presents multivalued logic modelsdifferences and roles for managing uncertainty in expert system for evaluating learning management systems evaluation and finally Section 4 presents the conclusion.

2. Multivalued Logic Modelsfor Managing Uncertainty in Expert System

This section explores definition, basic properties and differences of multivalued logic models for handling uncertainty.

2.1 Type 2 Fuzzy Set

Type-2 fuzzy set is a fuzzy set whose membership degree is fuzzy set. Type-2 fuzzy sets are useful when it is difficult to determine the exact membership function for a fuzzy set. This set can be used in problem state when there is uncertainty about the membership degree themselves [8]. Type-2 fuzzy set is used to express linguistic information from experts when membership functions are determined on uncertain numerical data [17] [18]. A Type-2 set U is characterized by a three dimensional membership function which itself is fuzzy as follows [18][19] :

$$\mu A\colon U(x, u) \rightarrow [0, 1], \text{ where } 0 \leq U(x, u) \leq 1. \qquad (1)$$

Type2 fuzzy inference system is presented in processes as fuzzification of input, inference engine, reduction and defuzzification as shown in Figure 1.Fuzzy knowledge base contains the membership functions of the interval fuzzy sets and set of type 2 fuzzy production rules. In fuzzification, the crisp input is converted to a fuzzy output using the membership functions stored in the fuzzy knowledge base. Type-reducer is when type-2 fuzzy set is reduced to type-1 fuzzy set. There are many type-reduction methods such as Karnik-Mendel and centroid. In defuzzificztion, the fuzzy output is converted to a crisp output using techniques such as centroid, and bisector.

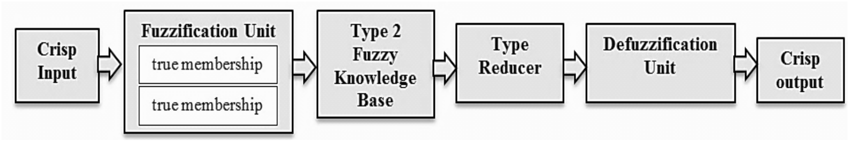

Figure 1. Block Diagram of Type2 Fuzzy Inference System

2.2 Intuitionistic Fuzzy Set

Atanassov the introducer of intutuitionistic fuzzy set said that the idea was a coincidence as he added to the fuzzy set definition a second degree which is a degree of non-membership. Atanassov's supervisor proposed the name intuitionistic fuzzy set because the way of fuzzification contains the intuitionistic idea as it incorporates the degree of hesitation [18]. An intuitionistic fuzzy set describes the relationship of an element to a set, so that the sum of these degrees is always less or equal to 1. An intuitionistic fuzzy set A = {<u, μA(u), vA(u) > |u ∈U} in a universe of discourse U is characterized by a membership function μA, and a non-membership function vA, as follows [19] [20]:

$$\mu A: U \rightarrow [0, 1], vA : U \rightarrow [0,1], \text{and } 0 \leq \mu A(u) + vA(u) \leq 1. \qquad (2)$$

In fuzzy set theory, the membership of an element to a fuzzy set is a single value between zero and one. However, in reality, it may not always be true that the degree of non-membership of an element in a fuzzy set is equal to 1 minus the membership degree because there may be some hesitation degree. According to Husain et al. [22]; intuitionistic fuzzy set is suitable in simulating human understanding in imprecise decision making Figure 2 shows the intuitionistic fuzzy inference system. Fuzzy knowledge base contains the true and false membership functions of the intuitionistic fuzzy sets and set of intuitionistic fuzzy production rules.

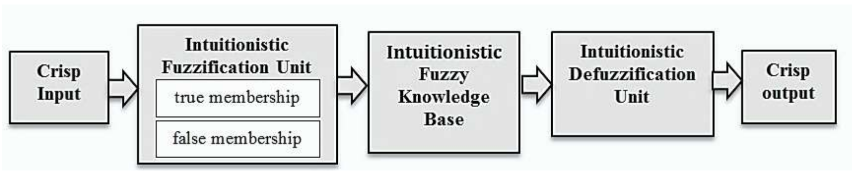

Figure 2. Block Diagram of Intuitionistic Fuzzy Inference System

2.3 Vague Set

Vague sets are based on the idea of the degree of membership μ of an element to a set and of non-membership of that element to the same set. Vague set V in a universe of discourse U is characterized by a true membership function αV, and a false membership function βV. As follows [19] [21]:αV :

$$U \rightarrow [0, 1], \beta V : U \rightarrow [0, 1], \text{and } \alpha V(u) + \beta V(u) \leq 1. \qquad (3)$$

A vague set, as well as an intuitionistic fuzzy set, is a further generalization of a fuzzy set. Figure 3 shows vague inference system consisting of vaguification unit, vague knowledge base, and devaguification unit. Vaguification is a mathematical process that determines the input degree of belongingness in form of membership functions. After vaguifying the input, system knows the degree of membership and degree of opposition. Based on the degrees, vague inference engine evaluates the rules defined in rule base. Devaguification is the process to convert the multiple output values into a crisp number.

The difference between intuitionistic fuzzy set and vague set can be shown in the next example [21]: suppose in a testing region a set of ten sensors and ten corresponding measurements are obtained {20, 22, 20, 21, 20, -, 20, 20, -, 20} at a certain time t.The true membership is 0.6, and the false membership is 0.2. For number 20 (i.e. 1- β = 0.8), the true membership is 0.1. For number 21 and number 22, the false membership is 0.7 (i.e. 1- β = 0.3). Therefore, the vague set= [0.6, 0.8]/20+[0.1,0.3]/21+[0.1,0.3]/22,where the intuitionistic fuzzy set= {< 20, 0.6, 0.2 >, < 21, 0.1, 0.7 >, < 22, 0.1, 0.7 >}.

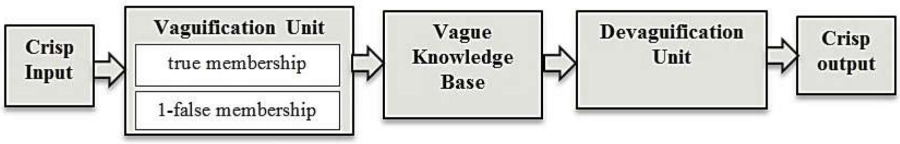

Figure 3. Block Diagram of Vague Inference System

2.4 Neutrosophic Set

Smarandache [11] proposed a new approach called neutrosophic logic as an extension of fuzzy logic. Neutrosophic logic is better option to simulate human thinking than fuzzy logic because unlike fuzzy logic, Neutrosophic logic is able to handle indeterminacy of information which expresses the percentage of unknown parameters [17]. Neutrosophy comes from Latin "neuter", which means neutral and Greek "Sophia", which means skill or wisdom. It means knowledge of neutral thought[11].

Neutrosophic logic is an extension of the fuzzy logic, intuitionistic logic, and the three-valued, allof which variable x is described by triple values x= (t, i, f) where t is the degree of truth, f is the degree of false and i is the level of indeterminacy. The next example points that neutrosophic set is more natural than previous sets described in some applications. The proposition "Tomorrow it will be raining" does not mean a fixed-valued components structure; this proposition may be 40% true, 50% indeterminate and 45% false at a time; but at in a second timemay change at 50% true, 49% indeterminate, and 30% false (according with new evidences, sources, etc.). Fuzzy set, vague set and intuitionistic fuzzy set cannot express this example [23]. Expert systems, decision support system, belief system, and information fusion ~~tends~~ to rely not only on truth value, but also on falsity membership. So current systems which are dedicated to simulate human brain are constrained with strict conditions, whereas, neutrosophic logic holds its chance to simulate human thinking and to be utilized for real world executions [22].neutrosophic logic is able to deal with contradictions which are true and falseas the sum of components any number between –0 and 3+ [11].

Neutrosophic inference system consists of neutrosophication unit that accepts the crisp input and assigns the appropriate membership functions, neutrosophic knowledge base that maps input to output variable, and deneutrosophication unit that maps neutrosophic value to crisp value as shown in Figure 4 [17]. Neutrosophic knowledge base contains the membership functions of neutrosophic sets (true, indeterminacy, false) and neutrosophic rule base. Neutrosophication unit accepts the crisp input and assigns the appropriate membership (truth, indeterminacy, false). Then input variables are mapped to output using the Neutrosophic rule base. The resulting Neutrosophic output is mapped to crisp value indeneutrosophication step using defuzzification methods. Neutrosophic set can handle indeterminate information; when an expert is asked about certain statement to give a degree that the statement is true, degree the statement is false; and degree of indeterminate [23].

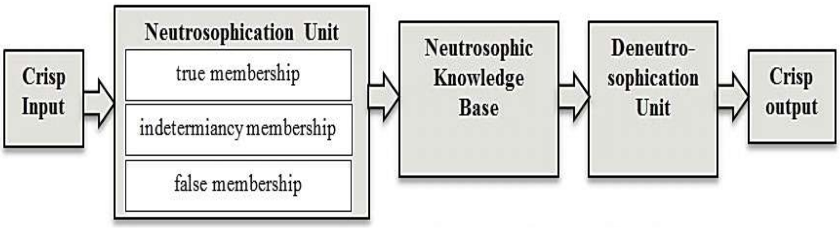

Figure 4. Block Diagram of Neutrosophic Inference System

3. Managing Uncertainty in Expert System for Evaluation of Learning Management System

A better understanding of the differences and use between the uncertainty models is presented in this section. The selection of the appropriate uncertainty model for a problem is essential to get the desirable results. As mentioned in introduction section, the primary uncertainties types are *vagueness* which includes information that normally vague; for example "the color of the flower is nearly red", *imprecision* when available information is not specific value ; for example "the temperature of the machine is between 88-92 °C " , *ambiguity* when information is unclear; for example, "Votes for this candidate is about 60%", and *inconsistence* when obtainable information is conflicted or undetermined; for example " the chance of raining tomorrow is 70%, it does not mean that the chance of not raining is 30%, since there might be hidden weather factors that is not aware of". A comparison analysis proposed to compare the multivalued logic models in terms of the originator, year, hesitancy source membership function and uncertainties types that models can handle [24][25][26][27][28], is shown in Table 1. The Fuzzy set describes vagueness, Type-2 fuzzy set is an extension of fuzzy sets which describes vagueness and imprecision by a range of membership values. Intuitionistic fuzzy set is suitable in simulating imprecision in human thinking. Vague set is more natural than the intuitionistic fuzzy set to represent unclear information. Neutrosophic set can deal with vagueness, imprecision; ambiguity and inconsistent information exist in real world. It can be concluded that there is no ideal model to express uncertainty in expert system; it all depends upon the available data, information, and knowledge for the unsolved problem.

Learning Management Systems (LMSs) are web based application used to manage e-learning process. The use of these applications has increased in higher education as it assists students and instructors to design, share and deliver learning materials [29][30]. Many universities considered LMSs as a useful tool that support in spreading educational resources to the learners [30][31]. LMS system quality is described by development organizations with imprecise, vague, ambiguity and inconsistent terms. That is why traditional evaluation methods may not be virtuous. System quality is a wide concept that is associated with system performance and user interface [30]. Previous researches show that system quality is an important determinant of user satisfaction and perceived usefulness can be defined as the stability, reliability and suitability of the system [31]. System quality includes other attributes such as usability, availability, response time and adaptability attributes [32]. Previous studies in learning management system evaluation are implemented under complete information, while real environment has uncertainty aspects. . That is why traditional evaluation methods may not be virtuous.This leads us to suggest the multivalued logic approaches such as type2 fuzzy, intuitionistic fuzzy, vague and neutrosophic models, all of which give better attribute interpretations to evaluate LMSs. In Table 2, a proposal for applicability of fuzzy, type 2 fuzzy, intutuionistic fuzzy, vague and neutrosophic expert system for evaluating LMS systems that concern three attributes which are usability, reliability, and accessibility.

Table1. Comparison of Multi-valued Logic Models

	Fuzzy set	**Type 2 Fuzzy**	**Intuitionistic Fuzzy**	**Vague**	**Neutrosophic**
Originator	LotfiZadeh, 1965	LotfiZadeh, 1975	Atanssov, 1983	Gau and Buehrer, 1993	Smarandache, 1999
Hesitancy Source	Degree of cognition	Degree of for evidences and against evidences	Degree of for evidences and against evidences	Degree of for evidences and against evidences	Degree of for evidences, Indeterminacy and against evidences
Membership Function	Degree of belonging	Fuzzy member-ship function	Degree of membership function and non-membership function	Degree of membership function and non-membership function	Degree of membership function, indeterminacy and non-membership function
Types of Uncertainities	Vagu enes	Vaguness, Imprecision	Vaguness, Imprecision	Vaguness, Imprecision, Ambiguity	Vaguness, Imprecision, Ambiguity, Inconsistent

Table2. Multi-Valued Logic Models Memberships Functions in Expert Systems for Evaluation of Learning Management Systems

		Type2 Fuzzy	Intuitionistic Fuzzy	Vague	Neutrosophic
Usability	Efficiency Learnability Memorability Error Tolerance User Satisfaction	$\mu_{Low}(x,u)$ in [0,1], $\mu_{Medium}(x,u)$ in [0,1], $\mu_{High}(x,u)$ in [0, 1], Where $\mu(x,u)$ is membership function.	μ_{Low} (x) in [0,1], V_{Low} in [0,1], $\mu_{Medium}(x)$ in [0,1], V_{Medium} in [0,1], $\mu_{High}(x)$ in [0,1], $V_{High}(x)$ in [0,1], Where $\mu(X)$ is membership function, V(x) is a non-membership function and $0 \le \mu(x) + V(x) \le 1$.	μ_{Low} (x) in [0,1], 1-β_{Low} in [0,1], $\mu_{Medium}(x)$ in [0,1], 1-β_{Medium} in [0,1], $\mu_{High}(x)$ in [0,1],1-$\beta_{High}(x)$ in [0,1], Where $\mu(x)$ is membership function, $\beta(x)$ is a non-membership function and $0 \le \mu(x) + \beta(x) \le 1$.	$T_{Low}(x)$, $I_{Low}(x)$, $F_{Low}(x)$, $T_{Medium}(x)$, $I_{Medium}(x)$, $F_{Medium}(x)$, $T_{High}(x)$, $I_{High}(x)$, $F_{High}(x)$, Where T(x) is membership/truth value, I(x) is indeterminacy value, F(x) is a non-membership/False value.
Reliability	Fault Tolerance Maturity Recoverability	$\mu_{Low}(x,u)$ in [0,1], $\mu_{Medium}(x,u)$ in [0,1], $\mu_{High}(x,u)$ in [0, 1], Where $\mu(x,u)$ is membership function.	μ_{Low} (x) in [0,1], V_{Low} in [0,1], $\mu_{Medium}(x)$ in [0,1], V_{Medium} in [0,1], $\mu_{High}(x)$ in [0,1], $V_{High}(x)$ in [0,1], Where $\mu(X)$ is membership function, V(x) is a non-membership function and $0 \le \mu(x) + V(x) \le 1$.	μ_{Low} (x) in [0,1], 1-β_{Low} in [0,1], $\mu_{Medium}(x)$ in [0,1], 1-β_{Medium} in [0,1], $\mu_{High}(x)$ in [0,1],1-$\beta_{High}(x)$ in [0,1], Where $\mu(X)$ is membership function, $\beta(x)$ is a non-membership function and $0 \le \mu(x) + \beta(x) \le 1$.	$T_{Low}(x)$, $I_{Low}(x)$, $F_{Low}(x)$, $T_{Medium}(x)$, $I_{Medium}(x)$, $F_{Medium}(x)$, $T_{High}(x)$, $I_{High}(x)$, $F_{High}(x)$, Where T(x) is membership/truth value, I(x) is indeterminacy value, F(x) is a non-membership/False value.

4. Conclusion

The paper reviews various approaches to handle uncertainty in expert systems. Each multivalued logic model has its interest and properties. It cannot be concluded that an approach is ideal for any expert system. It all depends upon the available information and problem needed to be solved. The paper presents a better understanding of the differences between the multivalued logic models in managing uncertainty in expert systems. Discussing the uncertainty models adds value to select the appropriate model for a problem and get the desirable results.

Classical probability, Bayes theory, Dempster–Shafer theory and fuzzy set presented by previous researches for handling uncertainty information in expert systems, but these models are cannot express different types of uncertainties. Bayesian works well where accurate statistical data are obtainable. However, in many expert system applications the accurate statistical data is not available. Dempster–Shafer presents belief functions which permit the experts to use their knowledge to bind the assignment of probabilities when boundaries aren't available, but it does not give direction on how to obtain these assignments. Therefore, there is not any expert systems build using this theory. Certainty Factor is as type 1 Fuzzy set, uncertain data as is expressed as a membership degree in a crisp value between 0 and 1. Fuzzy set does not express the degree of non-membership and it has not a solution when experts have a hesitancy to define membership. The Fuzzy set describes vagueness, but not imprecision, ambiguity, and inconsistent.

Type-2 fuzzy set is an extension of fuzzy sets in which vagueness and imprecision are expressed by a range of membership values; it expresses uncertainty by a range of membership values but this does not reveal the concept of variability. A limitation of type-2 fuzzy system is complexity and high cost of computational time.

Intuitionistic fuzzy is as vague set, present fuzzy objects naturally, and show the concept of variability. In addition vague set simulate ambiguity human understanding in decision making. For example,

“Ahmed is tall” is given by an interval in the unit interval [0.6, 0.8]. In intuitionistic fuzzy set, this means 60% of a given population declares that Ahmed is tall while 20% does not. (Another 20% is neutral). While in vague sets, this means 60- 80% of a given population declares that Ahmed is tall**.**

Neutrosophic set can deal with vagueness, imprecision; ambiguity and inconsistent information exist in real world as neutrosophic idea is based on indeterminacy. For example; a vote with two symbols which are: A-ballots and B-ballots is occurred, in which some votes are deteriorated, and it can’t be determined if it’s written A or B. These are indeterminate votes that could be expressed with neutrosophic logic. Therefore, Human thinking indeterminacy can be handled by neutrosophic logic while other approaches neglect this point.

Furthermore, the study provides insights for the utilization of multivalued logic models in expert system to evaluate learning management systems. Future work will deal with quality evaluation of LMSs described by uncertain terms. Neutrosophic Logic is a new approach for evaluating the system quality attributes of various systems that can adapt variations and changes. This is an assertion to use neutrosophic logic approach for assessing the system quality of LMSs.

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