The Use of "Fuzzy Logic" for Identifying Significant Environmental Aspects

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It is a major challenge to assess environmental, health and safety risks in the mostly non-quantitative world of environmental management. It is an even greater challenge to communicate these risks to stakeholders. Given the imprecise methods currently available to rank risk, there is a fundamental need to formalize human judgment and perception when identifying significant environmental aspects to be included in an ISO 14001 environmental management system.

This edited version of a paper from the 2001 AESF/EPA Conference for Environmental Excellence presents an approach for using "fuzzy logic," an artificial intelligence technique, as an alternative to numerical methods. Instead of providing black-and-white answers based on "gray" data that are subject to human judgment or perception, fuzzy logic allows for the mathematical modeling of qualitative data and provides answers that are more consistent with the real world. Fuzzy logic makes it possible, therefore, to model the descriptive and simplistic measures often used in audit reports, and can help environmental managers identify significant environmental aspects with greater company-wide consistency and control.

You have just completed a marathon meeting with the CEO and the Director of Operations, who fully support the development and implementation of an environmental management system (EMS) for the facility. As the EH&S manager, you have just been assigned the task of steering this process. You have been reading up on what an EMS is, and over the past several years you have followed the ISO 14001 standard development. The one thing that has never been clear to you is how to determine what constitutes a "significant" environmental aspect. You have heard dozens of presentations on how to identify and rank environmental issues as part of an EMS; however, there always seems to be this gray area defining the word "significant." Complicating the terminology are the various opinions and perceptions of those involved in the EMS process.

Realizing you will never gain complete agreement on which issues are "significant" and which issues are not, you ask yourself the question: "How can I set out to identify significant environmental aspects in a way that incorporates the various stakeholders' opinions and perceptions?" You realize that the plant manager, vice president of operations, and the facility environmental manager are going to be asking:

- "Which aspect is most important?"
- "What is the likelihood that each aspect will lead to a fine?"
- "How much will it cost to fix each finding?"

These are good questions and there are metrics to use in developing a ranking system to allow for the identification of "significant" environmental aspects. They are subjective and qualitative terms, however, without a numerical system.

The relative accuracy of each value assigned to these and other categories will depend on a variety of factors, including your experience with regulatory officials in similar situations, the facility's commitment to its environmental, health and safety programs, and what the organization's goals are in developing an EMS.

Whether you or the facility personnel realize it, you have just relied on non-quantitative data to form an opinion and rank risk—an opinion that will likely have an impact on capital costs and long-term operating costs. Therefore, the question remains, "Did we make the decision that is consistent with company-wide practices and that accurately defines our risk?" Binary responses, such as yes or no, are easy for the auditor to provide, but rarely accepted by facility personnel.

Quantitative responses, such as $100,000, or "the regulators will find this to be the number one," are often desired by the facility personnel. This creates a communication

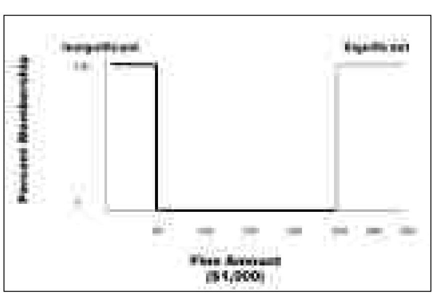

Fig. 1—Crisp set membership.

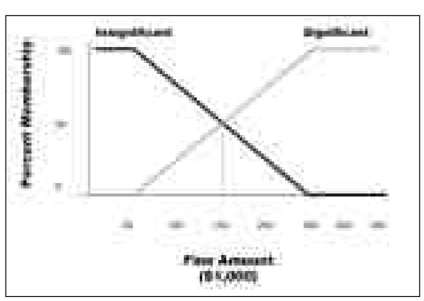

Fig. 2—Fuzzy set membership.

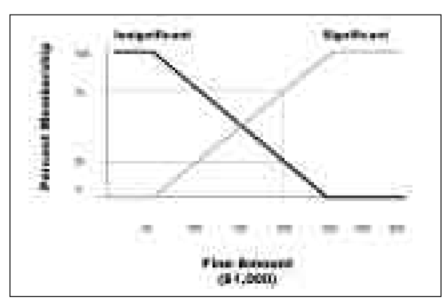

Fig. 3—Fuzzy set membership.

barrier between the auditor and auditee. To bridge this gap, an auditor commonly uses more descriptive, non-quantitative terms—such as "highly likely," "minor threat," "low potential risk," or "significant cost"—to describe risk. Using a ranking system incorporating the terms described above, an auditor may base his or her audit findings on biased information.

In many instances, risk associated with non-quantitative terms is ranked using criteria such as health/safety, environmental impact, enforcement threat, and corrective action costs. For each audit finding, a numerical value is typically assigned to each criterion. For example, a ranking system between 0 and 3 could be used where 0 represents a situation with insignificant risk and 3 represents a significant risk. Through simple mathematical analysis, a score for each finding is calculated by totaling the ranking for each criterion, which is used to prioritize all of the findings. Such risk ranking systems have been used extensively throughout the environmental compliance industry to evaluate EH&S audit results, determine significant environmental aspects when developing an environmental management system (EMS), and to track improvements associated with auditing and environmental management programs.

But, beware! The definitions of the non-quantitative terms are often vague, and the quantitative values assigned to the non-quantitative terms are often subjective. Worse yet, the eventual prioritization of combined quantitative values for non-quantitative terms can skew the results and multiply uncertainty. As Albert Einstein once said, "Not everything that counts can be counted, and not everything that can be counted, counts."

This points to the need to develop a ranking system free from such error. Enter fuzzy logic. Fuzzy logic is a form of set theory that allows an auditor and an audited facility to address the ambiguity associated with non-quantitative risk and to avoid the loss of accuracy or meaning when combining results. It allows the results to be presented in terms of possibilities as opposed to probabilities. Following is a brief and general comparison of probability and fuzzy logic set membership.

Fuzzy Logic: An Overview

Fuzzy logic is a form of artificial intelligence that is based on varying degrees of set membership. In essence, everything is a matter of degree, including truth and set membership.[1] Fuzzy logic provides mathematical calculations to estimate the degree to which something, someone, or somewhere belongs, in part, to a set or group of sets. It is difficult to discuss fuzzy logic without first mentioning the inherent philosophical differences between probability and set membership. As a philosopher, Aristotle developed *The Three Laws of Thought,* which, as a result, established the "crisp" boundaries for all mathematical fields of study. Until the introduction of "fuzzy logic," Aristotle's first law, the *Law of Identity*—the primary axiom of Aristotelian logic—remained mathematically unchallenged.[2] The *Law of [crisp] Identity* is presented below and compared to *The Law of Fuzzy Identity:*

The Law of [crisp] Identity:
If statement P is true, then P is true. If a thing, A, is A, then it is A.

The Law of Fuzzy Identity:
If not-A is 80% of W, then A is 20% of W. A thing, A, is A relative to not-A. Therefore, A = (A, not-A).

In the real world, it is nearly impossible to discuss set membership or the probability of an event occurring without using verbal approximations. Terms such as a "significant" regulatory fine and an "insignificant" regulatory fine have a variety of meanings based on a host of variables. For example, they depend on company size, operating budget, or the perception of the interpreter. If the words significant and insignificant were defined by "crisp" values, the following might be true: Significant is $250,000 fine, and Insignificant is $50,000, as shown in Fig. 1. In the "crisp" world of audit results, a finding would belong or not belong to the set of Significant or Insignificant. This presents a problem for the majority of audit findings that fall somewhere between the boundaries set for regulatory fines. Even if another category entitled "Moderately Significant" were added with values between $50,001 and $249,999, there would still remain a vertical or "crisp" boundary between each of the three categories.

Table 1A Aspects

Aspect No.	Aspect Description	Potential/Actual Threats
[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]

Table 1B Input Data

Aspect	Health/Safety	Environmental Impact	Public Relations
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]

Table 2 Numerical Based System Results

Finding No.	Health/Safety	Environmental Impact	Public Relations	Average Score
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

If the potential for a Significant or Insignificant regulatory fine were defined by "fuzzy" values, the assigned values for Significant and Insignificant would remain the same (*i.e.,* $250,000 and $50,000, respectively). However, there could be a tolerance for partial membership to each set. That is, the potential for a $150,000 fine may be 50% Significant and 50% Insignificant, as shown in Fig. 2. This may seem inconsequential. When implementing a numerical risk ranking system using "crisp" non-quantitative terms, however, the likelihood of compounding error by combining criterion scores is much greater.

Fuzzy logic defines a world of ambiguities.[3] This is an important concept when considering our desire to incorporate bivalent computers into our multivalent lives. As humans, we are able to reason based on vague terms, whereas a computer relies on zeros and ones to compute. Fuzzy logic bridges the computing/reasoning

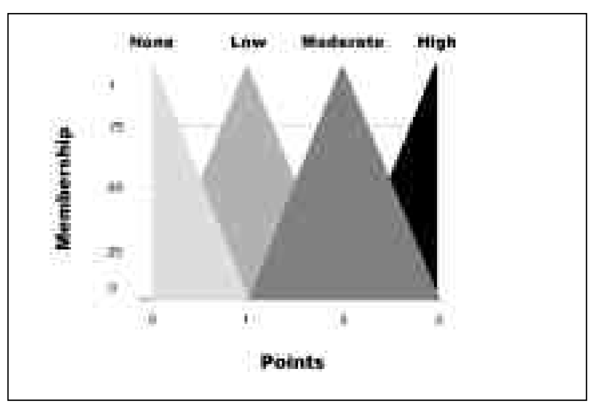

Fig. 4—Fuzzy membership diagram.

gap and provides engineers with the ability to incorporate expert knowledge into common, everyday appliances such as vacuums, washing machines, cars, and many other products. In addition, fuzzy logic provides the ability to incorporate better and more sensitive analytical evaluation techniques and controls for engineered systems, such as pumps, trains, car transmissions, and chemical mixers. The notion central to fuzzy systems is that membership values are indicated by a value on the range [0.0, 1.0], with 0.0 representing absolute falseness and 1.0 representing absolute truth.[4]

For example, consider the statement: "Finding x may be subject to a significant fine." Say the potential fine amount is $200,000. Based on Fig. 3, we would assign a truth value of 0.75 to the above statement. Therefore, the statement could be translated into fuzzy set terminology as follows:[5] "Finding x is a member of the set of Significant Fine." This statement would be rendered symbolically as a fuzzy set, as: mSignificantFine(Finding x) = 0.75, where m is the membership function, operating in this case on the fuzzy set of Significant Risk, which returns a value between 0.0 and 1.0.[6]

It is important to distinguish between fuzzy systems and probability. Both operate over the same numeric range, and at first glance, both have similar values: 0.0 representing false (or non-membership), and 1.0 representing true (or membership). In contrast to fuzzy logic theory, probability theory is a formal examination of the likelihood (chance) that an event will occur, measured in terms of the ratio of the number of expected occurrences to the total number of possible occurrences. Therefore, probability or stochastic methods describe a process in which imprecise or random events affect the values of variables, so that results can be given only in terms of probabilities.[7]

The distinction between probability theory and fuzzy logic theory can be made by replacing the fuzzy logic statement of the previous example with a probability statement. The probabilistic approach yields the natural-language statement: "There is a 75% chance that Finding x will receive a Significant Fine." While the fuzzy terminology states: "The membership Finding x within the set Significant Fine is 0.75."

The major difference between the two statements is that the probability approach excludes partial membership to the set of Significant Fine, whereas the fuzzy approach accommodates partial membership. Although the probability approach may not present an issue when discussing certain variables, it can be problematic when dealing with engineering solutions or process control loops. When fuzzy logic is used in a control loop, therefore, it affords various levels of control given the measured parameters, such as temperature, pressure, and flow.

It is also important to note the operational differences between probabilistic operations and fuzzy logic operations. For independent events, the probabilistic operation for "and" is multiplication, which is counter-intuitive for fuzzy systems.[8] For example, say that x = Finding x, E is the fuzzy set of Environmental Impact, and T is the fuzzy set of Threat to Health and Safety. Then, if mE(x) = 0.90 and uT(x) = 0.90,[9] the probabilistic result would be: mE(x) * uT(x)=0.81 whereas, according to fuzzy logic, the result would be: MIN[mE(x), uT(x) = 0.90]. As seen from this example, the probabilistic calculation yields a result that is lower than both of the two initial values. This could present a problem when analyzing and combining several variables.

Table 3 Input Data as Fuzzy Membership Numbers

Finding No.	Health/Safety	Environmental Impact	Public Relations
I	High	Low	High
II	Low	Moderate	Moderate
III	Low	Moderate	Low
IV	Low	Low	Low

Table 4 Partial Set of Output Rules *

Rule No.	IF	THEN
1	Health/Safety = High	Aspect = Significant
2	Environmental Impact = High	Aspect = Significant
3	Environmental Impact = Moderate AND Health/Safety = Moderate	Aspect = Significant
4	Environmental Impact = Moderate OR Health/Safety = Moderate	Aspect = Evaluate in Future
5	Environmental Impact = Low to None OR Health/Safety = Low to None	Aspect = not significant

* Rules reflect sensitivity toward health and safety issues

Table 5 Fuzzy-Based Results

Aspect No.	Rule No.	Health/Safety	Environmental Impact	Public Relations	Aspect
I	1	High	Low	High	Significant
II	2	Moderate	High	Moderate	Significant
III	4	Moderate	Low	Moderate	Evaluate in Future
IV	[illegible]	High	Moderate	Low	Not Significant

Applying Fuzzy Expert Systems

Fuzzy expert systems use fuzzy logic as opposed to Boolean logic. In other words, a fuzzy expert system is a collection of membership functions and rules that are used to apply reason to data. Unlike conventional audit ranking systems, which are basic mathematical equations, fuzzy expert systems focus on numerical processing. That is, the criterion (health/safety, environmental impact, etc.) defined in the audit ranking system can be used as input variables to derive output values that also have membership sets. The system would then rely on a set, or multiple sets, of rules. A simple example of a rule in a fuzzy expert system is as follows: IF x is Low AND y is High, THEN z is Medium. In this statement; x and y are input variables, (*i.e.*, names for known data values), z is an output variable (*i.e.*, name for a data value to be computed), Low is a membership function defined on x, High is a membership function defined on y, and Medium is a membership function defined on z. In the above equation or rule, the part of the rule between the IF and the THEN, which says "x is Low AND y is High" is considered the premise or antecedent. This is a fuzzy logic expression that describes to what degree the rule is applicable. The part of the rule following the THEN, which says "z is Medium" is considered the conclusion or consequence. This part of the rule assigns a membership function to each of one or more output variables. Most tools for working with fuzzy expert systems allow more than one conclusion per rule, thereby resulting in a rule-base or knowledge-base system.

Establishing a rule-based system is beneficial in the following ways:

- It allows the auditor to apply his or her experience in assessing a numerical score for each criterion related to each audit finding (the input variables).
- Based on the score, non-quantitative terms can be used to describe each audit finding.
- In some cases, most importantly, it provides the opportunity for a group of people to develop a consensus-based set of definition for input and output values, as well as the rules that determine the results, thus, providing a knowledge-based audit system consistent with company-wide practices that accurately defines the associated level of risk.

Example

The following illustrates the differences between using a fuzzy- or knowledge-based audit ranking system and a numerical-based ranking system to determine significant environmental impacts. Both examples will use a ranking system with a value ranging from 0 to 3 for four criteria, which are Health/Safety, Environmental Impact and Public Relations. The ranking system values and definitions are as follows:

Health & Safety

0—No identified potential risk to Public Health. No need for immediate corrective action to protect Public Health.
1—Low potential risk to Public Health. Need for long-term corrective action plan to protect Public Health.
2—Moderate potential risk to Public Health. Need for timely corrective action to protect Public Health.
3—High potential risk to Public Health. Need for immediate corrective action to protect Public Health.

Public Health and Safety Risk is evaluated considering both the health and safety of the general public and that of staff. Therefore, consideration is given to both the number of employees working at the facility and to the population density in the area of the site.

Environmental Impact

Findings are rated for their potential impact to four classes of environmental media (soil, groundwater, surface water, and air). The EMS team may choose to evaluate the potential impact to each media separately before proceeding with the overall evaluation. For the purpose of this example, assume that such an exercise has been conducted and the overall impact to the environment will be evaluated according to the following criteria:

0—No Actual or Potential Impact.
1—Low to Moderate Potential Impact: No Actual Impact.
2—Moderate to High Potential Impact: Low to Moderate Actual Impact.
3—High to Major Potential Impact: Moderate to High Actual Impact.

Public Relations

Each finding is rated as follows:

0—Good Management Practice.
1—Low probability of negative publicity resulting from the violation (Minor issue of noncompliance with regulatory standards).
2—Moderate probability of negative publicity resulting from the violation (Major issue of noncompliance with regulatory standards).
3—High probability of negative publicity resulting from the violation (for example, an enforcement action would be taken).

Aspect Summary

The hypothetical finding information is presented in Table 1A and 1B.

Numerical-based System Results

To determine the average score for each finding in the numerical-based system, the values for each criterion are added, and then divided by the number of criteria, which in this example is three.

Knowledge-based (Fuzzy) System Results

To compute the results for this example, fuzzy membership diagrams must be developed for each criterion similar to Fig. 4. Next, the input data from Table 1 must be converted into fuzzy membership numbers, which are presented in Table 3. Then, a consensus-based set of rules must be developed to combine the fuzzy numbers for specific criterion into results that can be prioritized. A sample set of rules is presented in Table 4 and the results for each finding are presented in Table 5. Note that using a fuzzy, or knowledge-based system results in a broad range of priorities. Some findings have moderate priorities, while others have urgent priorities.

Summary

Opinion and perception are key discriminators that factor into an aspect analysis. In this example, the values for each aspect and the rules used to classify the results were selected by the author for demonstrative purposes. The core values embraced by individual organizations will result in a different set of metrics providing varying outputs. When comparing the results from the two approaches, however, it should be clear that the knowledge-based example provides a greater sense of meaning with regard to both the input data and the results. In addition, the use of output rules allows for the prioritization of results based on real-world factors, or variables that may vary among different facilities under the same operating group, different industry classes in the same geographic area, and similar facilities in different states or countries.

Author's note: It should be noted that this is a simplified application of fuzzy logic. The true value of such an evaluation comes when the auditor is allowed to enter data in decimal format using a sliding scale or scroll bar, instead of the discrete values 0, 1, 2, or 3. In doing so, this increases the number of available input values within the same evaluation range. Therefore, each potential aspect could maintain partial membership to more than one criterion. Combining partial memberships requires that the boundaries of each criterion be mathematically defined such that the degree of partial membership can be determined. Finally, the output rules would be modified to reflect this greater level of sensitivity, and a more involved level of fuzzy mathematics would be applied. *P&SF*

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