# ENVIRONMENTAL EVALUATION: FUZZY IMPACT AGGREGATION

P. N. SMITH

The University of Queensland, Australia

#### **ABSTRACT**

This article reviews some of the theory of fuzzy sets or subsets and illustrates, by way of a simple example, an application to environmental impact assessment.

# INTRODUCTION

Environmental impact assessment (EIA) is a formalized approach for assessing the positive and negative impacts of a development project on human welfare and on the environment and provides information which can be used to determine whether project characteristics conform to statutory requirements or are perceived as being acceptable [1]. The range of methodologies available to assist EIA can be classified as *identification* methods, *predictive* methods or *evaluation* methods [2]. Identification methods commonly record the presence or absence of impacts, while predictive methods estimate the likely magnitude of impacts distributed in space and time. Evaluation methods attempt to assess the "aggregate worth" of projects in human and environmental terms. These are commonly either qualitatively- or quantitatively-oriented. Each approach has its advocates, though a middle ground approach has been proposed [3].

Evaluation methods often employ the additive weighting format, which involves forming the weighted sum of quantified environmental impacts. For example, the Battelle Environmental Evaluation System [4] and methods proposed by Odum [5], Sondheim [6], and Prasartseree [7] are examples of additive weighting. In addition, Allett proposed an additive weighting method which involved aggregating environmental impacts distributed spatially in terms of a grid system [8].

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Additive weighting facilitates the aggregation of diverse impacts, a process common to the whole range of techniques falling under the rubric of multicriteria analysis (MCA). MCA has become of increasing interest in recent years, and some accounts and/or reviews include Keeney and Raffia [9], Nijkamp [10], Nijkamp and Van Delft [11], Rietveld [12], Nijkamp and Spronk [13], Hwang and Yoon [14], Zeleny [15], Goicoechea et al. [16], Voogd [17], Roy [18], Hwang and Lin [19], Massam [20], and Nijkamp et al. [21].

In an environmental impact assessment context, often only one project is examined in terms of consequences for the environment, although discrimination between a set of projects, such as alternative road alignments, or alternative transit options, to identify the project having the least impact is also common. However, even in the case of a single project, comparison should always be made with the "do-nothing" or "status quo" situation.

Explicit recognition of uncertainty or imprecision has been a component of some EIA methodologies, particularly additive weighting. For example, Odum et al. [22] proposed a variant of the additive weighting methodology which permitted weighted scores to vary by 50 percent in either direction. Kahne [23, 24] developed a similar Monte Carlo approach in the context of MCA, but also applicable to EIA. While methods based on probability theory are of value in representing uncertainty, an alternative means of characterizing imprecision and uncertainty involves fuzzy sets.

Fuzziness is a type of deterministic uncertainty and although fuzziness shares many similarities with randomness, represented by probability theory, it is conceptually and theoretically distinct from randomness [25, 26]. The source of fuzziness in a fuzzy set is the absence of precisely defined class membership and not uncertainty concerning membership of an object in a set. Fuzzy mathematics based on fuzzy sets and fuzzy logic more adequately acknowledges the vagueness, inexactitude, imprecision, and fuzziness characteristic of EIA and decision making than conventional quantitative mathematics.

#### ADDITIVE WEIGHTING

The environmental impact assessment of projects may be considered in terms of scores  $\phi_{ij}$  for project  $P_i$  and environmental characteristic or impact category  $I_j$ . Typically, weights  $\{w_1, w_2, \ldots, w_j\}$  are introduced to represent the differential importance of impact categories. The impacts,  $\phi_{ij}$ , may be measured on *nominal*, *ordinal*, *interval* or *ratio* scales [27].

The basic format of additive weighting is as follows

$$V_i \; = \; \Sigma_j \; w_j v_j (\varphi_{ij})$$

where  $V_i$  is the aggregate impact of project  $P_i$ ,  $w_j$  is the relative importance of impact category  $I_j$ ,  $\phi_{ij}$  is the score of project  $P_i$  with respect to impact category  $I_j$ ,  $v_j($ ) is some standardization, normalization, performance or value function, and

the  $\phi_{ij}$  are measured on at least an interval scale. The  $v_j()$  functions account for the positive or negative orientation of impact categories. For example, "electricity generation" (say, in 1000 kilowatts per hour) is considered to be positive in the sense that higher values are more desirable for both human welfare and the environment. Conversely "air pollution" is considered to be negative in the sense that higher values (say, CO emissions in parts per million) are less desirable for human welfare and the environment.

The commonly adopted form of additive weighting assumes no uncertainty or imprecision in outcomes and/or weights. However, Odum [5], Odum et al. [22], and Kahne [23, 24] relax this assumption. The approach of Odum is expressed as

$$V_{i}^{(k)} = \sum_{i} (e_{ii}^{(k)} + 0.5) w_{i} \phi_{ij} \phi_{i}^{*}$$

where  $V_i^{(k)}$  is the kth iteration of the total impact index for project  $P_i$ ,  $w_j$  is the relative importance of impact category  $I_j$ ,  $\phi_{ij}$  is the score of project  $P_i$  with respect to impact category  $I_j$ , and  $\phi_j^* = \max_i \{\phi_{ij}\}$ .  $e_{ij}^{(k)}$  is a uniform random number for project  $P_i$  and impact category  $I_j$  on the kth iteration. All impacts are assumed negative. Since  $0 \le e_{ij}^{(k)} \le 1$ ,  $(e_{ij}^{(k)} + 0.5)$  will vary between 0.5 and 1.5. This variation was permitted in the absence of a priori knowledge concerning impact variability. The mean value and standard deviation of  $V_i^{(k)}$  ( $k = 1, 2, \ldots$ ) were used to order projects in terms of aggregate environmental impact.

Kahne developed a similar Monte Carlo approach in the context of MCA, but also applicable to EIA. This was expressed as

$$V_i^{(k)} = \Sigma_i \omega_i^{(k)} \rho_{ii}^{(k)}$$

 $R_{ij}$  is a set of real numbers (e.g., the interval [7-10] or [1-3]) with elements  $\rho_{ij}$  in the set expressing the variability in performance of project  $P_i$  with respect to impact category  $I_j$ . The  $\rho_{ij}$  are assumed to be uniformly distributed in the interval  $R_{ij} = [a_{ij}, b_{ij}]$  with cumulative distribution function  $F_R(\rho_{ij}) = (\rho_{ij} - a_{ij})/(b_{ij} - a_{ij})$ .  $W_j$  is a set of real numbers (e.g., the interval [1-3] or [5-7]) with elements  $\omega_j$  expressing the variability in importance of impact category  $I_j$ . The  $\omega_j$  are also assumed to be uniformly distributed in the interval  $W_j = [c_j, d_j]$  with cumulative distribution function  $F_w(\omega_j) = (\omega_j - c_j)/(d_j - c_j)$ . At each iteration k, a random number r in the interval [0, 1] is generated and the inverse transformations,  $\rho_{ij}^{(k)} = F_R^{-1}(r) = a_{ij} + r(b_{ij} - a_{ij})$  and  $\omega_j^{(k)} = F_W^{-1}(r) = c_j + r(d_j - c_j)$  applied for each impact category, multiplied together and summed to form  $V_i^{(k)}$ . The frequency distribution of  $V_i^{(k)}$  may be used to identify that project with minimal overall environmental impact.

# **FUZZY SETS**

An alternative approach to acknowledging uncertainty involves the concept of fuzzy sets. The fundamental concept in mathematics is that of a set—a class or collection of objects. Objects (or elements) are assigned to sets because they share

properties or conform to a rule. Examples of sets include the set of odd integers, {1, 3, 5, ...} and the set of real numbers greater than 7, {x|x>7}. Conventional, classical or *crisp* sets contain objects that satisfy precise properties required for membership, e.g., the set of integers between 1 and 5, {1, 2, 3, 4, 5}. The integer 2 belongs to this set and the integer 9 does not. Crisp sets are characterized by a membership function which assumes the value 1 if an object belongs to the set and 0 otherwise, and correspond to two-valued logic—is or is not, yes or no, 1 or 0. Fuzzy sets contain objects that satisfy imprecise properties to varying degrees, e.g., the set of integers close to 7. The integer 6 belongs to this set to a greater degree than the integer 10. Fuzzy sets are characterized by a membership function assuming values from 0 (complete non-membership) to 1 (complete membership) and correspond to a continuously-valued logic. The membership function is the basic idea in fuzzy set theory; its value represents the degrees to which objects satisfy imprecisely defined properties.

Some general discussions of fuzziness and fuzzy mathematics include Zadeh [28-31], Kickert [32], Leung [33], Dubois and Prade [34], Schmucker [35], Kandel [36], Novak [37], Zimmermann [38], Kosko [25] and Klir and Folger [39]. Basic introductory texts on fuzzy sets include [38, 40-42].

The age of human beings might be defined in terms of a base set [0, 100] years on which the linguistic terms of "old," "young," "middle-aged," "very old," etc. might be defined as labels of fuzzy sets (Figure 1). Similarly, linguistic terms such as "medium" may be expressed on a base set of real numbers (say, the interval [0, 1]) as numbers in the base set close to 0.5. Thus fuzzy sets labeled as "medium" and "close to 0.5" are equivalent. On this base set, "high" might be represented by numbers close to 1 and "low" as numbers close to 0.

The base set of objects (age, numbers), on which linguistic terms are defined, is context dependent. For example, "young" in the context of the age of Huon pine trees which live for several hundred years would be defined on a different base set than for the age of human beings. Further, a "short" distance in a neighborhood context is defined differently than a "short" distance in a regional context and "small" in the context of quantum mechanics is defined differently than "small" in the context of astronomy.

In terms of expressions of the performance of projects with respect to environmental impact categories, the base set used in the example below is the interval [0, 1], but equally the interval [0, 10] or [0, 100] might be used. Linguistic terms, have meaning within the base set of objects (numbers).

A fuzzy set A in a set X (a collection of objects denoted generically by x) is a set of ordered pairs  $A = \{(A(x), | x \in X) \text{ where } A(x) \text{ is called the membership (grade of membership, degree of compatibility, degree of truth) of x in A which maps X into a membership space, usually the [0, 1] interval [28, 36]. A simplified representation of a fuzzy set A when X is finite is <math>A = \sum A(x)|x|$  where the sigma notation indicates union rather than sum. Formally, a fuzzy set is a mapping  $A: X \to Z$  where Z is the membership grade domain which Zadeh [28] assumes to

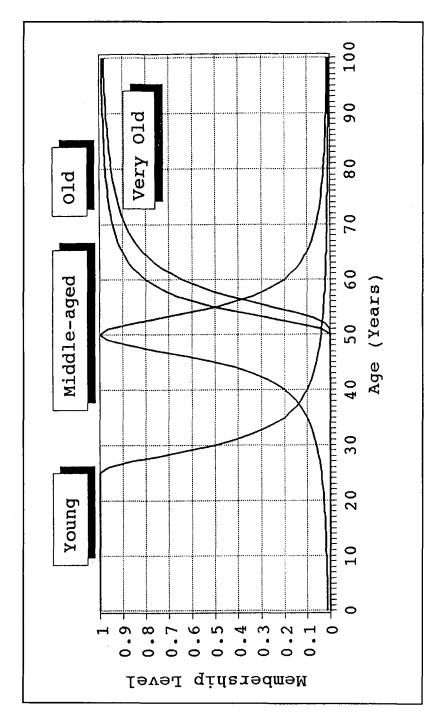


Figure 1. Fuzzy sets-"Young," etc.

be the unit interval Z = [0, 1]. For crisp sets,  $Z = \{0, 1\}$ . Thus, in the classical case, Z consists of only two possible degrees of membership, namely complete membership (1) and complete non-membership (0).

When the base set X is not finite, an appropriate notation is  $\mathbf{A} = \int_X \mathbf{A}(\mathbf{x})/\mathbf{x}$  where the integral sign indicates union. Thus the fuzzy subset  $\mathbf{A}$  of X is continuous rather than pointwise. A fuzzy number is a fuzzy set which is usually assumed to have the properties of both normality and convexity [34, 43, 44]. Normality requires that the maximum membership of the fuzzy subset in  $\mathbf{R}$  (which may not be unique) is 1; that is, that at least one real number is fully contained in the subset. Convexity ensures that the membership function will be piecewise continuous and that at the point (or interval) where the membership function is equal to 1, the membership function will be nondecreasing on the left and nonincreasing on the right. Thus the membership function exhibits peakedness in the vicinity of its highest point (or interval) [45]. A fuzzy number may be represented as  $\mathbf{M} = (m_1, m_2, m_3, m_4)$  (Figure 2). Particular types of fuzzy numbers include trapezoidal fuzzy numbers (where  $m_1 < m_2 < m_3 < m_4$ ) and triangular fuzzy numbers, where  $m_1 < m_2 = m_3 < m_4$ , and fuzzy numbers based on S- and  $\Pi$ - functions [30, 46]. These fuzzy numbers are illustrated in Figure 3.

In terms of a performance space, say the interval [0, 1], suitably defined fuzzy numbers (here fuzzy numbers based on Π- and S-functions) may be assigned linguistic values such as "low," "medium," and "high" (Figure 4). In addition, hedges might be introduced such as "very" and connectives such as "not." Hedges modify primary linguistic values such so that terms such as "very high" and "not low" are possible. In Figure 4, fuzzy numbers have been used to represent "very high" and "very low."

### **FUZZY ADDITIVE WEIGHTING**

In terms of fuzzy variables a form of additive weighting may be expressed as follows

$$V_i = \{ \begin{array}{c} J \\ \oplus w_j \otimes \phi_{ij} \end{array} \} \quad \bigoplus J, \qquad i = 1, \dots, I$$

where  $V_i$  denotes the fuzzy aggregate impact of project  $P_i$ ,  $w_j$  denotes the fuzzy relative importance of impact category  $I_j$  defined in the interval [0, 1],  $\phi_{ij}$  denotes the fuzzy performance of project  $P_i$  with respect to impact category  $I_j$  defined in the interval [0, 1], and  $\otimes$ ,  $\oplus$  and  $\oplus$  denote fuzzy multiplication, fuzzy addition and fuzzy division, respectively. The  $\phi_{ij}$  here denote the performance of projects such that the positive and negative orientation of impacts are considered.

Algebraic or arithmetic manipulation of fuzzy numbers (such as the multiplication and addition operations in fuzzy additive weighting) is based on the *extension principle* [46]. The extension principle permits any algebraic operation

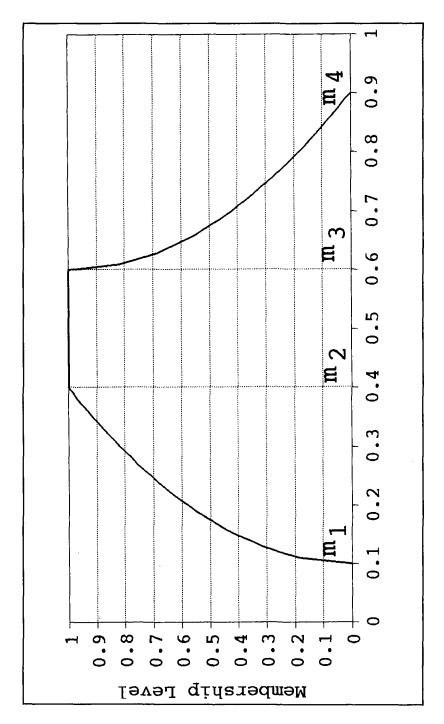


Figure 2. Fuzzy number M.

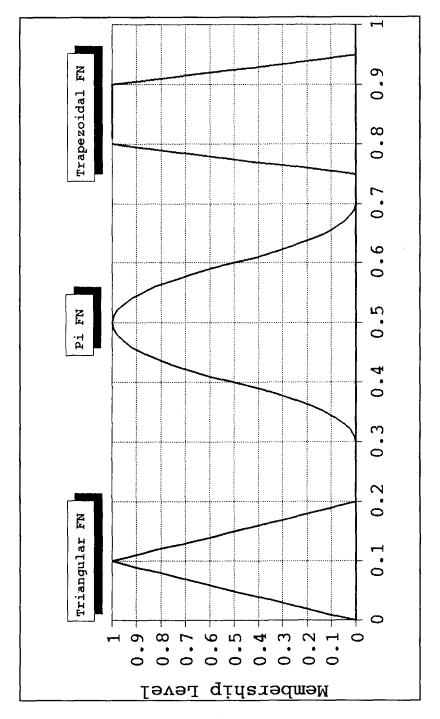


Figure 3. Fuzzy numbers.

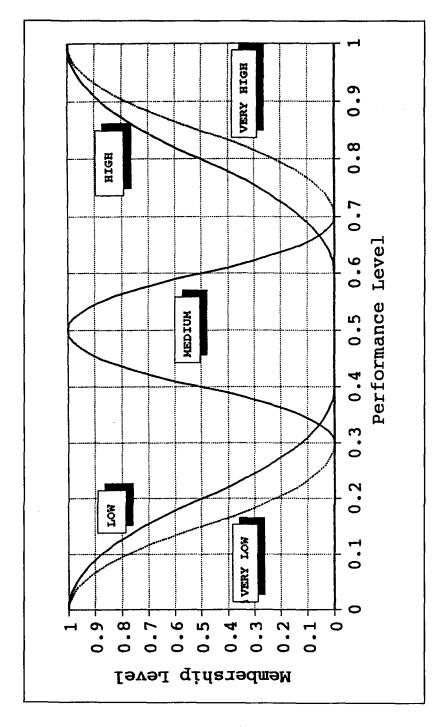


Figure 4. Fuzzy numbers "very low" to "very high."

defined for non-fuzzy sets to be extended to fuzzy subsets, referred to as extended algebraic operations. The extension principle, though well defined is difficult to compute and various approaches have been devised, including standard fuzzy arithmetic [42] used in the example below.

# Example

Consider 4 projects (route alignments) and 7 impact categories as follows:

I<sub>1</sub>: Impact on water quality

I2: Travel time savings

I<sub>3</sub>: Impact on land values

I4: Impact on flora

I<sub>5</sub>: Impact on fauna

I<sub>6</sub>: Noise impact

I<sub>7</sub>: Construction, acquisition, maintenance costs

Assume impacts as illustrated in Impact Matrix 1 where the entry in a given cell represents the performance of a project  $P_i$  (row) with respect to an impact category  $I_j$  (column) and "VL" = "very low," "L" = "low," "M" = "medium," "H" = "high," and "VL" = "very high." Project  $P_i$  is the most environmentally sensitive and most costly, while project  $P_4$  is the least environmentally sensitive and least costly. Projects  $P_2$  and  $P_3$  are somewhere in between. Assume weights as follows,  $\{w_1, w_2, w_3, w_4, w_5, w_6, w_7\} = \{L, M, M, M, M, L, L\}.$ 

The aggregate impacts, based on fuzzy additive weighting, are illustrated in Figure 5 which suggests that the ordering of projects in terms of performance (least environmental impact) is  $P_1 > P_2 > P_3 > P_4$ . The detail of these calculations are given elsewhere, together with procedures for more formally identifying an ordering of projects [47]. In Figure 5 the fuzzy numbers (dotted lines) to the right and left represent, respectively, the best possible (all outcomes VH) and the worst possible (all outcomes VL) performances under the weighting scheme given. These represent bounds on the possible performance of projects.

		I,		I,	Ic	I,	I,
P <sub>1</sub>	H	٧L	М	н	н	н	VL
P <sub>1</sub>	L	М	М	М	м	м	ւ
P <sub>1</sub>	H	L	н	VĽ	м	L	м
Pi	VL	н	VL	L	м	VL	H
Weight	. <b>L</b>	М	М	H	Н	L	L

Impact Matrix 1

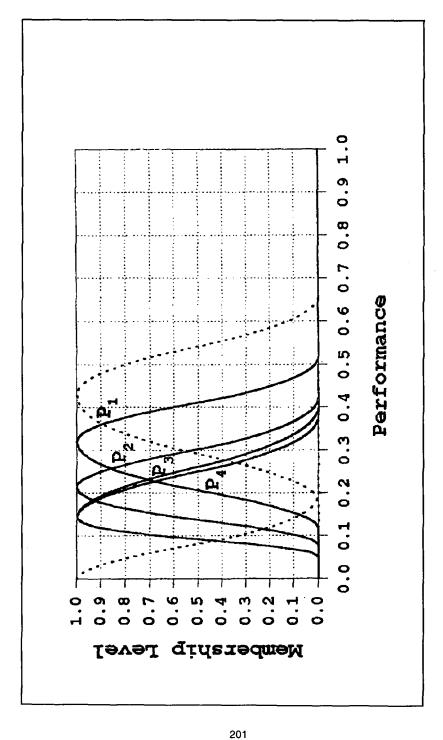


Figure 5. Fuzzy overall performances.

#### CONCLUSION

A method of fuzzy additive weighting has been presented which is appropriate in the context of qualitative linguistic statements of the performance of projects in terms of defined impact categories. In addition, linguistic expressions of importance are used to weight impacts. Linguistic expressions of project performance and the importance of impact categories are labels of fuzzy sets (fuzzy variables) defined on a [0, 1] base set.

The resolution or "granularity" of the performance and importance dimensions involved five levels ("very low," "low," "medium," "high," "very high"). However, a finer resolution might allow for other linguistic expressions such as "low to medium," "medium to high," and "very very high." The level of granularity appropriate to given contexts requires further exploration, as do the precise definition of the fuzzy sets involved, and assessing ways to identify a crisp ranking of projects in terms of environmental impact [47].

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# Direct reprint requests to:

P. N. Smith
Department of Geographical Sciences and Planning
The University of Queensland
St. Lucia, Queensland
Australia 4072