An Integration of Quantitative and Qualitative Decision Support for Environmental Impact Assessment

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Abstract

A complicated decision-making problem such as environmental impact assessment usually requires both quantitative and qualitative decision support tools to collaborate for reaping their benefits concurrently. Although the analytic hierarchy process (AHP) has been widely used in EIA, it is hardly to address the dependence issue among environmental factors and reflect the subjectivity between science and societal values and beliefs. This paper proposes an integrated model to incorporate fuzzy analytic network process (quantitative decision support) with fuzzy logic (qualitative decision support) for managing environmental impact assessment. Finally, the proposed approach was applied to the EIEs of construction projects, exemplified in a case study of the Taiwan High-Speed Rail project.

1. Introduction

In decision theory, there are three types of decision-making: (1) structured, (2) unstructured and (3) semi-structured [24]. Structured decision-making is well defined, clearly understood and routine in nature, and can be addressed by following a set of standard operating procedures, data processing and management-science models. Structured decision-making can be handled by means of quantitative decision support tools such as analytic hierarchy process (AHP) [18] or analytic network process (ANP) [19]. On the other hand, unstructured decision-makings cannot be addressed by using standard operating procedures because it often has its basis in human intuition, judgment, knowledge, and adaptive problem-solving behavior. Qualitative decision support methods such as fuzzy logic [26] appear more suitable for dealing with unstructured decision-making. Semi-structured decision-making, having both structured and unstructured elements, is a combination of both standard solution procedures and human judgment. Environmental impact assessment (EIA) is such a complex semi-structured decision-making because it should not only consider the scientific aspect (quantitative decision-making) but also reflect political values and social acceptability (qualitative decision-making). Therefore, integrating quantitative and qualitative decision support tools for EIA is the focus of this paper.

EIA can be defined as the systematic identification and evaluation of the potential impacts (effects) of proposed projects, plans, programs, or legislative actions relative to the physical-chemical, biological, cultural, and socioeconomic components of the total environment [4]. The EIA process essentially involves scoping, studying baseline conditions, identifying potential impacts, predicting significant impacts, and evaluating them. Scoping determines which components are to be included in the EIA and alternatives to be considered. A baseline condition, namely the existing environment, is recognized as a benchmark by which the future conditions of project alternatives are compared. Historically, several methodologies have been developed for the identification of impacts on the baseline condition, including the ad hoc, overlay, checklist, matrix, and networks methods. The purpose of impact prediction is to forecast the effects of an identified impact through methods such as subjective judgment, case studies, quantitative mathematical models, statistical models, pilot models and experiments. Once an impact has been forecasted, it is necessary to evaluate it.

Traditionally, the use of AHP has become a significant trend in EIA due to its capability for facilitating multi-criteria decision-making. For example, Tsamboulas and Mikroudis [15] devoted themselves to the combination of the AHP with cost-benefit analysis methods to develop an overall assessment of the impacts of transport initiatives over different geographical regions and time periods. Ong et al. [22] used the AHP method to assess the environmental impact of materials process techniques by deriving a single environmental score based on process emissions for each of the products or alternatives evaluated. In order to compare three large industrial development alternatives in an orderly manner, Sòlnes [21] applied the AHP to calculate the environmental quality index of each. Readers are referred to Ramanathan's [16] discussion on the advantages and shortcomings of using the AHP for environmental impact assessment.

Despite the popularity of the AHP in EIA, it should be noted that the AHP makes three critical assumptions [8]. First, the relevant criteria form a hierarchical decision system and remain independent of each other. Second, the relevant criteria are well defined; hence, their scores are easily evaluated. Third, the relevant criteria and their associated weights are certain. However, these assumptions are not agreeable to the properties of EIA depicted below.

- **Dependences among environmental factors.** The environmental factors involved in EIA can be roughly grouped into three categories: environmental pollution, ecological alteration and socioeconomic disturbance. The developments of human society and economics produce environmental pollution leading to further changes in the ecology. However, environmental pollution and destroyed ecology also increasingly impair human socioeconomic progress. These environmental factors are obviously interdependent; i.e., they can partially influence each other to various extents. In this paper, 'dependence' is synonymous with 'influence.'
- **Subjectivity in EIA.** Two sources of subjectivity in EIA originate in estimating the relative importances of environmental factors and evaluating the impacts induced by a project. Both are concerned with balancing economic developments, environmental risk and societal values, in which considerable subjective judgment is required because expertise, in addition to political values and social acceptability, has a significant role. Therefore, the subjectivity is inevitable in EIA, as Kontic [12] stated: 'The influence of personal value systems and beliefs is unavoidable when creating an expert evaluation and interpretation (p.431).'
- **Fuzziness accompanied by subjectivity.** Fuzziness originates from the qualitative nature of human thinking. In EIA, concepts, values and judgments are usually expressed as linguistic terms that are inherently imprecise, vague, ambiguous or fuzzy.

The analytic network process (ANP) [19] relieves the independence limitation inherent in the AHP so that several researchers have been able to manipulate the dependence property of environmental factors. For example, according to data on the land cover, population, roads, streams, air pollution and topography of the Mid-Atlantic Region of the United States, Tran et al. [23] conducted an integrated environmental assessment by combining principal component analysis and the ANP. Chen et al. [5] introduced the use of the ANP to develop a decision model for evaluating potentially adverse environmental impacts of alternative construction plans. Although Mikhailov and Madan [14] have proposed a fuzzy extension of the ANP called fuzzy analytic network process (FANP), which allows fuzzy weights for dealing with imprecise human comparison judgments, there is still no published literature reporting the use of the FANP to appraise environmental impacts.

Due to its ability to imitate human capabilities that manipulate perceptions and subjectivities to draw conclusions, fuzzy logic [27], i.e., 'computing with words,' has been applied to a variety of problems in environmental science and management, including the modelling of eutrophication in Taihu Lake [6], decision support in ecosystem management [1], an evaluation of environmental impact indicators for the mixed cropping systems of the Inland Pampa [9], a performance evaluation of slow sand filters used for wastewater treatment [20], forecasting the possibility of next-day high-ozone levels (Heo and Kim, 2004), an integrated assessment of watershed conditions for sedimentation [7], and an assessment of sustainable development [2]. Borri et al. [3] introduced a fuzzy rule-based methodology for environmental evaluation which provided a robust tool to directly cope with linguistic models of human interpretation of environmental systems. Van der Werf and Zimmer [25], as well as Roussel et al. [17], endeavored to use fuzzy expert systems to calculate an indicator "Ipest" which reflects an expert perception of the potential environmental impact of the application of a pesticide in a crop field. Gonz´alez et al. [10] utilized fuzzy logic to avoid the need for in-depth environmental knowledge and extremely accurate data to implement the assessment, thus making life-cycle assessment more applicable to small and medium-sized enterprises.

To consider these three properties of EIA simultaneously, this study attempted to integrate fuzzy logic into (qualitative decision support tool) a fuzzy analytic network process (quantitative decision support tool) to establish a hybrid framework for evaluating environmental impacts. More specifically, this study sought to fulfil environmental impact evaluations by using fuzzy-set theory to model the fuzziness of the subjectivity, fuzzy analytic network process to manage the dependences among environmental factors and fuzzy logic to manipulate the subjectivity as experts do in an synthesized manner.

2. Evaluation Methodologies

2.1 Overall Evaluation Framework

An evaluation framework for the environmental impact of public infrastructure projects during construction is depicted in Fig. 1. This framework considers the overall impact determined by three major clusters: environmental pollution, ecological alteration and socioeconomic disturbance. The environmental pollution contains five indicators: air (I_1), water (I_2), soil (I_3), noise (I_4), solid waste (I_5); the ecological alteration contains two indicators: terrestrial (I_6), aquatic (I_7); the socioeconomic disturbance includes three indicators: economics (I_8), society (I_9) and culture (I_{10}). When assessing these ten indicators, the concept of 'acceptability' is employed because it can appropriately reflect the confluence between science and societal values and beliefs, which is a subjective and qualitative judgment. As shown in Fig. 1 (a), fuzzy logic is applied to infer the acceptabilities because it can bridge the gap between scientific measurement and the fulfilment of social objectives and provide a way to translate a wide variety of information - objective data, qualitative information, subjective opinions, and social needs - into a common language for characterising environmental effects (Silvert, 2000). The evaluation of acceptabilities of impacts related to these indicators is based on their respective sub-indicators. Air pollution evaluation refers to the appraisal of emission of carbon monoxide (CO), sulfur dioxide (SO_2), nitrogen dioxide (NO_2) and total suspended particulates (TSP); water pollution evaluation involves the conditions of dissolved oxygen (DO), biochemical oxygen demand (BOD), suspended solids (SS) and ammonia nitrogen (NH_3-N) in surface and ground water; soil pollution evaluation denotes liquid and gaseous chemical residues in soil; noise pollution evaluation indicates noise and vibration induced by construction equipment; solid waste evaluation implies rubbish and industrial waste from construction sites. The evaluation of threats to terrestrial species considers the threatened percentages of terrestrial animals, plants and endangered species; moreover, a similar evaluation focusing on aquatic species examines the threatened percentages of aquatic animals, plants and endangered species. Economic evaluation encompasses disturbances in land-use and development, life quality and economic activities. Societal evaluation considers inaccessibilities in public facilities and transportation, and disconnection in communities. Cultural evaluation encompasses destroyed cultural heritage and landscapes. The use of fuzzy logic to estimate the indicators is outlined in section 2.2.

An evaluation of the overall acceptability of the environmental impact based on these ten indicators involves three properties. First, the ten indicators crossing three clusters exist dependences to a certain extent. For example, a lower acceptability of water pollution can directly threaten terrestrial and aquatic habitats and somewhat restrain economic development, resulting in lower acceptabilities of ecological and economic conditions. Conversely, unacceptable economic developments usually cause more water pollution, which in turn leads to threatening natural habitats. Second, due to a lack of complete understanding of the interaction between indicators, it is difficult to accurately formulate the mechanism of dependence; therefore, expert subjectivity plays a significant role in assessing dependences among indicators. Third, fuzziness originates from the qualitative nature of human thinking. The degrees of dependences among indicators are usually expressed as in linguistic terms that are inherently fuzzy. To consider these three properties, this study utilised the fuzzy analytic network process [14] to evaluate the environmental impact on the basis of the ten indicators shown in Fig. 1 (b) and discussed in section 2.3.

2.2 Fuzzy Logic

Fuzzy logic [27] can be treated as a tool having the ability to compute with words for modeling qualitative human thought processes in the analysis of complex systems and decisions. In fuzzy logic, qualitative perception-based reasoning is represented by 'IF-THEN' fuzzy rules. The rule set concerning the acceptability of air pollution can be exemplified as

Rule 1: IF CO concentration is high AND SO_2 concentration is high AND NO_2 concentration is high AND TSP concentration is high THEN acceptability of I_1 is very unacceptable.

Rule 2: IF CO concentration is high AND SO_2 concentration is high AND NO_2 concentration is high AND TSP concentration is medium THEN acceptability of I_1 is unacceptable.

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Rule 80: IF CO concentration is low AND SO_2 concentration is low AND NO_2 concentration is low AND TSP concentration is medium THEN acceptability of I_1 is acceptable.

Rule 81: IF CO concentration is low AND SO_2 concentration is low AND NO_2 concentration is low AND TSP concentration is low THEN acceptability of I_1 is very acceptable.

where 'CO concentration,' 'SO_2 concentration,' 'NO_2 concentration,' 'TSP concentration' and 'acceptability of I_1' are linguistic variables; 'high,' 'medium,' 'low,' 'very unacceptable,' 'unacceptable,' 'acceptable' and 'very acceptable' are their possible fuzzy values, as defined in Fig. 2.

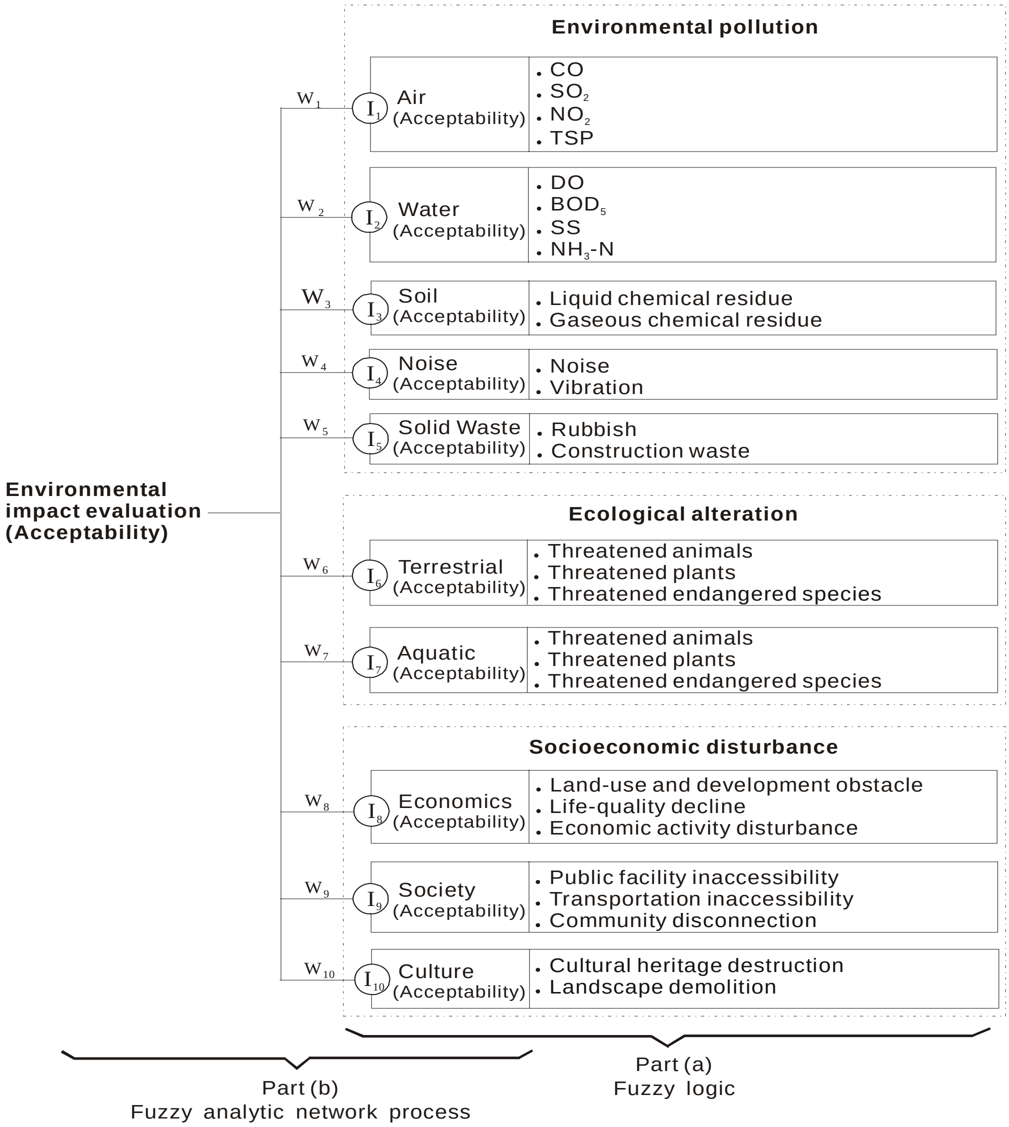

Fig. 1 An evaluation framework of environmental impact for public infrastructure projects during construction

When assuming that four factual statements (i.e., Fact 1: CO concentration is 5.6 ppm; Fact 2: SO_2 concentration is 9.1 ppb; Fact 3: NO_2 concentration is 31.8 ppb; Fact 4: TSP concentration is 187.0 $\mu g/m^3$) are fed into this inference mechanism, Mamdani's fuzzy reasoning [13] proceeds. Four major steps in reaching a conclusion using Mamdani's fuzzy reasoning are illustrated in Fig. 3 and described as follows.

Step 1: Computing compatibilities. Compatibility designates the similarity of an antecedent referring to a fact having the same linguistic variable or the suitability of a specific rule regarding several facts corresponding to the respective antecedents. For rule 80, the compatibility of Fact 1 with 'CO concentration is low' is 1.0; for Fact 2 with 'SO_2 concentration is low,' 1.0; for Fact 3 with 'NO_2 concentration is low,' 1.0; for Fact 4 with 'TSP concentration is medium,' 0.685. The overall compatibility of Rule 80 with the four facts is computed by a 'min' operator (i.e., minimum), thereby obtaining 0.685. Similarly, the compatibilities of Rules 81 with the same facts are 0.315. The overall compatibilities of rules 1 to 79 are not shown in Fig. 3 because these compatibilities are equal to zero.

Step 2: Truncating conclusions. Once the compatibility for each rule has been calculated, the degree to which the antecedents have been satisfied for each rule is known. As shown in Fig. 3, a trapezoid conclusion is then inferred by truncating the triangular conclusion of each rule with its corresponding compatibility.

Step 3: Aggregating truncated conclusions. Several inferred conclusions having the same linguistic variable should be aggregated. Aggregation is the process by which the fuzzy sets representing the truncated conclusions of triggered rules are combined into a single fuzzy set. In Fig. 3, the final conclusion is aggregated by using the union of all truncated conclusions.

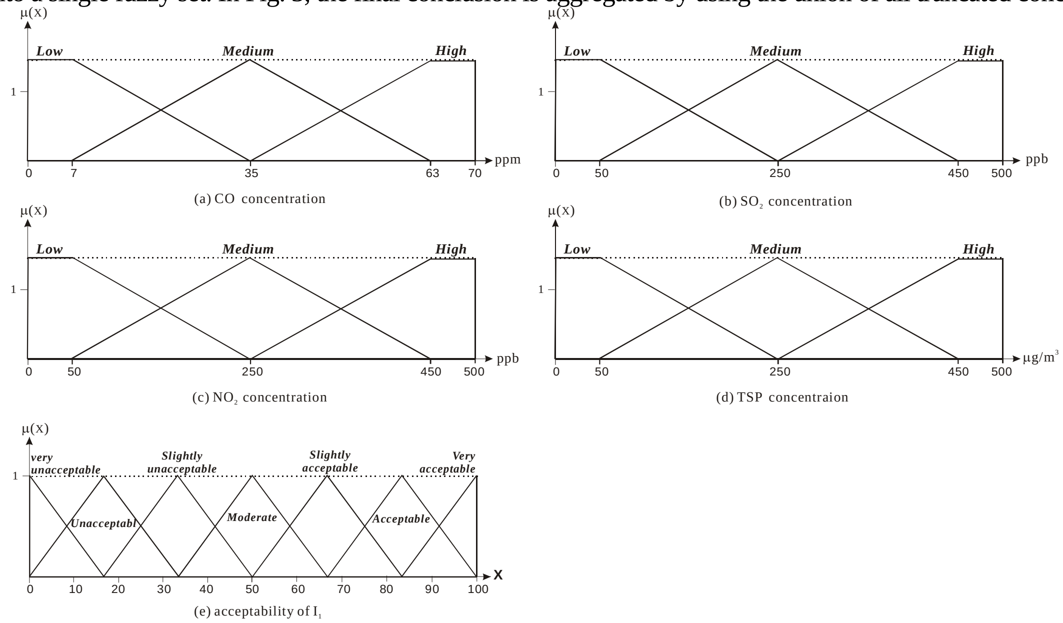

Fig. 2 Membership functions of fuzzy values for linguistic variables (a) CO concentration, (b) SO_2 concentration, (c) NO_2 concentration, (d) TSP concentration and (e) acceptability of I_1.

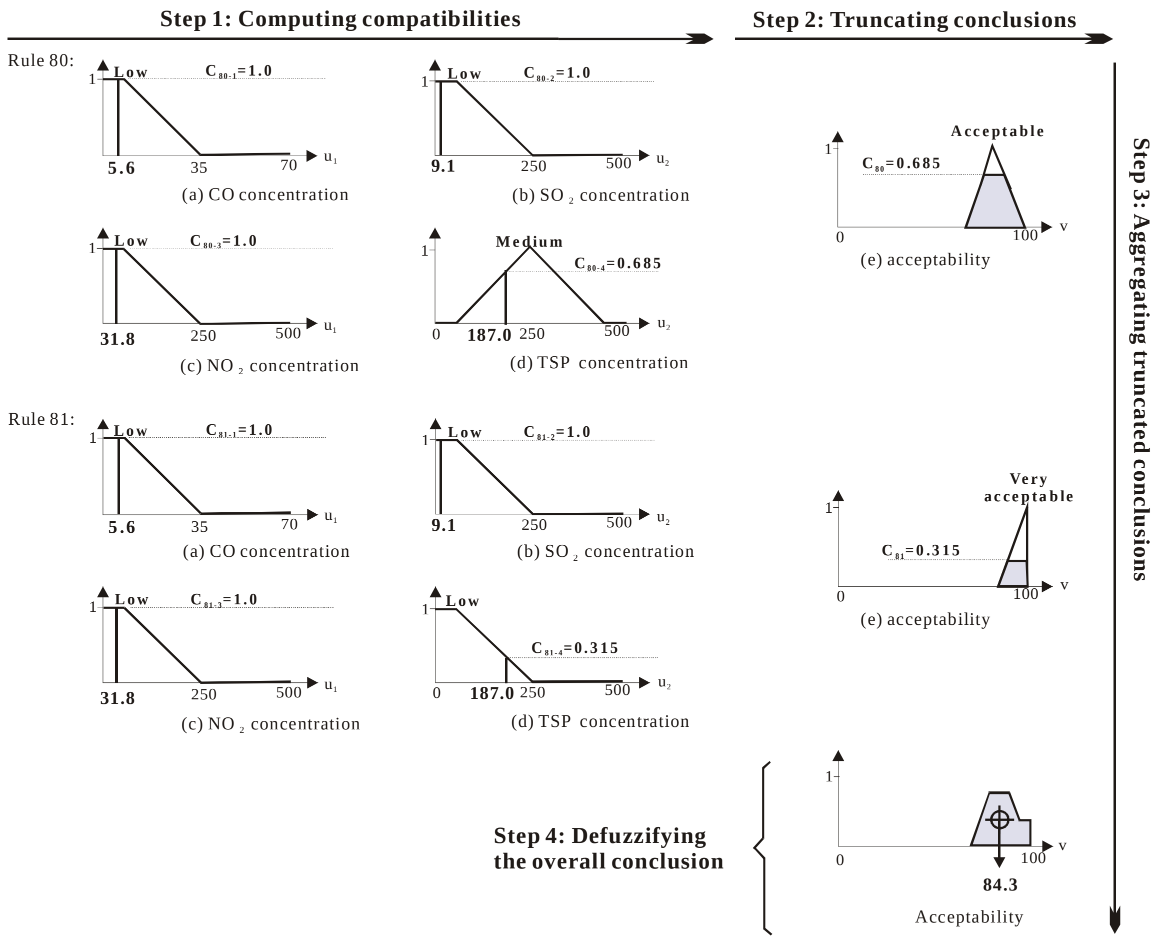

Fig. 3 Graphical representation of fuzzy reasoning

Step 4: Defuzzifying overall conclusion. In many cases, the final output of an inference system should be a single number. Defuzzification is a method to justifiably convert a fuzzy set into a precise value. This study utilised the center-of-gravity method, which takes the center of the area under the curve of the membership function of a fuzzy set as the answer. Fig. 3 indicates that the score of acceptability for air pollution is 84.3.

For evaluating the acceptabilities of the ten indicators, ten rule bases containing 252 fuzzy rules were produced: 81 rules for air (I_1); for water (I_2), 27; soil (I_3), 9; noise (I_4), 9; solid waste (I_5), 9; terrestrial (I_6), 27; aquatic (I_8), 27; economics (I_8), 27; society (I_9), 27; culture (I_{10}), 9.

2.2 The analytic network process (ANP)

The analytic network process (ANP) [19] extends the hierarchy structures in the AHP to networks so that dependence relationships among criteria can be manipulated. Similar to the AHP, the priorities in the ANP heavily rely on pairwise comparison, used to determine the influence of all criteria on a specific criterion. While comparing criteria, a natural way to represent comparison ratios is to use linguistic terms, thus reflecting the difficulty in expressing the preference of criteria by accurate numbers. Hence, the fuzzy analytic network process (FANP) [14] has been developed to tolerate fuzzy judgments in a pairwise comparison process, which can be summarized in seven steps.

Step 1: Developing a decision hierarchy. A hierarchical structure including the decision goal, clusters, criteria, subcriteria and lower elements is configured. In Fig. 1 (b), the goal environmental impact evaluation' is decomposed into three clusters (environmental pollution, ecological alteration and socioeconomic disturbance) and ten indicators (air (I_1), water (I_2), soil (I_3), noise (I_4), solid waste (I_5), terrestrial (I_6), aquatic (I_7), economics (I_8), society (I_9) and culture (I_{10})), where w_i is the relatively global weight of I_i with respect to the 'environmental impact evaluation' after considering the dependences among indicators. It should be noted that the global weights represent their relative influences; thus an indicator with a high global weight signifies high influences on other indicators. Conversely, an indicator is influenced largely by other indicators if it has a low global weight.

Step 2: Identifying dependences: influence network. The dependences among all components of the previous structure are identified; thus, the hierarchical structure becomes an influence network. The dependences within the same clusters are termed inner dependences; whereas, those crossing over different clusters are outer dependences. In Fig. 4, an arch from indicators I_i to I_j denotes that I_j is influenced by I_i, its attachment w_{ij}, an influence weight, represents the degree of influence which I_i exerts on I_j. For example, w_{26} and w_{28} represent the influence weights of water pollution with respect to terrestrial species and economic development, respectively. Conversely, w_{82} is the influence weight of economic development with respect to water pollution.

Step 3: Constructing influence matrices to weight dependences. To weight the dependences, a pairwise comparison of the components with fuzzy ratio judgments is applied. For example, to determine the influence weight w_{i2} of indicator Ii with respect to water pollution I_2, an influence matrix A_2 of pairwise comparison is constructed in Table 1. The entry a_{ik} of A_2, in fuzzy form, represents the relative influence of indicator I_i compared to indicator I_k on water pollution I_2. For example, in Table 1, a_{51} is $\tilde{5}$, thereby indicating that the influence of solid waste on water pollution is about five times that of air pollution.

Step 4: Deriving influence weights. A fuzzy preference programming method (Mikhailov and Madan, 2003) for calculating priorities from fuzzy pairwise comparison judgements is employed to derive influence weights from a fuzzy influence matrix. By an α-cut technique, this method decomposes a fuzzy influence matrix into a series of interval matrices; thus, a fuzzy linear programming approach is applied to solve the influence weights $w_{ij}(\alpha_k)$ for each α_k-cut level. Finally, all sets of influence weights are aggregated by Equation (1) as

$$w_{ij} = \frac{\sum_k \alpha_k w_{ij}(\alpha_k)\lambda_k^*}{\sum_k \alpha_k \lambda_k^*} \tag{2}$$

where λ_k^* is the consistency index for influence weights $w_{ij}(\alpha_k)$. Therefore, the influence weights w_{i2} of indicator I_i with respect to water pollution I_2 can be obtained on the basis of information from Table 1, the details of which are listed in Table 2.

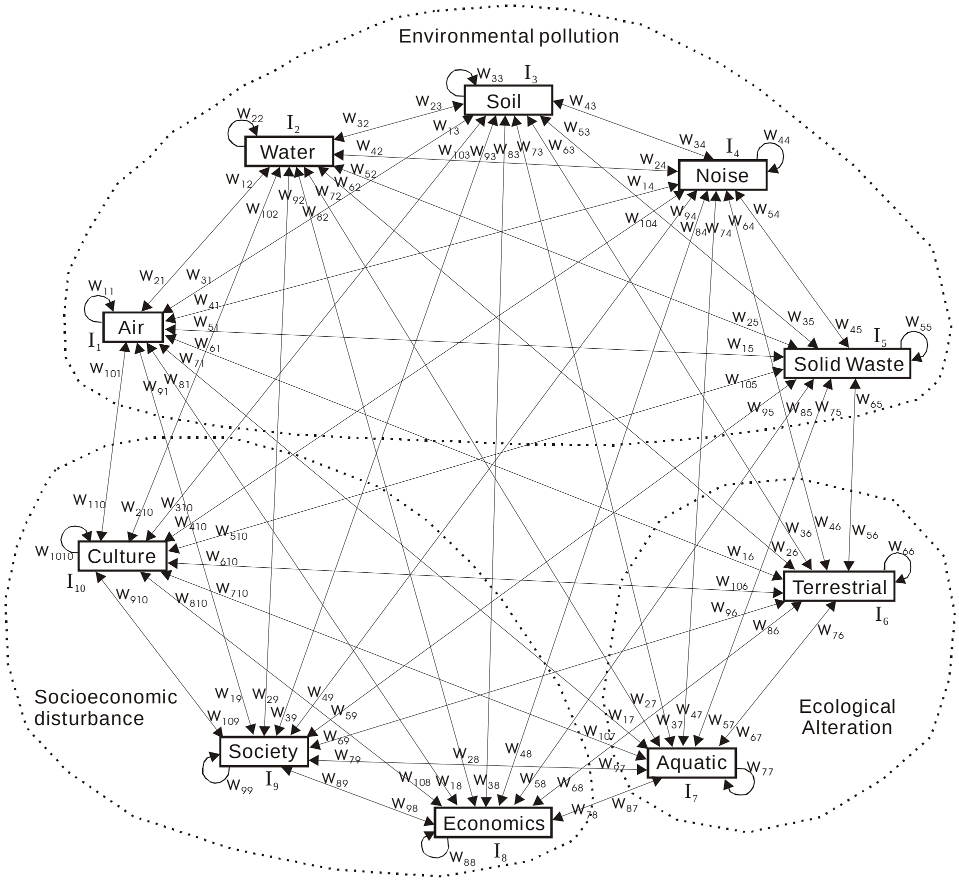

Fig. 4 Influence network

Table 1 Influence matrix for water pollution

Water	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}
Air (I_1)	1	$\frac{\tilde{1}}{35}$	$\frac{\tilde{1}}{5}$	$\tilde{2}$	$\frac{\tilde{1}}{5}$	$\tilde{1}$	$\frac{\tilde{2}}{3}$	$\tilde{2}$	$\tilde{2}$	$\tilde{2}$
Water (I_2)	$\widetilde{35}$	1	$\tilde{7}$	$\widetilde{65}$	$\tilde{7}$	$\widetilde{35}$	$\widetilde{25}$	$\widetilde{65}$	$\widetilde{65}$	$\widetilde{65}$
Soil (I_3)	$\tilde{5}$	$\frac{\tilde{1}}{7}$	1	$\widetilde{10}$	$\tilde{1}$	$\tilde{5}$	$\tilde{4}$	$\widetilde{10}$	$\widetilde{10}$	$\widetilde{10}$
Noise (I_4)	$\frac{\tilde{1}}{2}$	$\frac{\tilde{1}}{65}$	$\frac{\tilde{1}}{10}$	1	$\frac{\tilde{1}}{10}$	$\frac{\tilde{1}}{2}$	$\frac{\tilde{3}}{10}$	$\tilde{1}$	$\tilde{1}$	$\tilde{1}$
Solid waste (I_5)	$\tilde{5}$	$\frac{\tilde{1}}{7}$	$\tilde{1}$	$\widetilde{10}$	1	$\tilde{5}$	$\tilde{4}$	$\widetilde{10}$	$\widetilde{10}$	$\widetilde{10}$
Terrestrial (I_6)	$\tilde{1}$	$\frac{\tilde{1}}{35}$	$\frac{\tilde{1}}{5}$	$\tilde{2}$	$\frac{\tilde{1}}{5}$	1	$\frac{\tilde{2}}{3}$	$\tilde{2}$	$\tilde{2}$	$\tilde{2}$
Aquatic (I_7)	$\frac{\tilde{3}}{2}$	$\frac{\tilde{1}}{25}$	$\frac{\tilde{1}}{4}$	$\frac{\widetilde{10}}{3}$	$\frac{\tilde{1}}{4}$	$\frac{\tilde{3}}{2}$	1	$\tilde{3}$	$\tilde{3}$	$\tilde{3}$
Economics (I_8)	$\frac{\tilde{1}}{2}$	$\frac{\tilde{1}}{65}$	$\frac{\tilde{1}}{10}$	$\tilde{1}$	$\frac{\tilde{1}}{10}$	$\frac{\tilde{1}}{2}$	$\frac{\tilde{1}}{3}$	1	$\tilde{1}$	$\tilde{1}$
Society (I_9)	$\frac{\tilde{1}}{2}$	$\frac{\tilde{1}}{65}$	$\frac{\tilde{1}}{10}$	$\tilde{1}$	$\frac{\tilde{1}}{10}$	$\frac{\tilde{1}}{2}$	$\frac{\tilde{1}}{3}$	$\tilde{1}$	1	$\tilde{1}$
Culture (I_{10})	$\frac{\tilde{1}}{2}$	$\frac{\tilde{1}}{65}$	$\frac{\tilde{1}}{10}$	$\tilde{1}$	$\frac{\tilde{1}}{10}$	$\frac{\tilde{1}}{2}$	$\frac{\tilde{1}}{3}$	$\tilde{1}$	$\tilde{1}$	1

Step 5: Constructing a supermatrix. By reiterating step 4, all influence weights can be acquired to ultimately form an unweighted supermatrix, as presented in Table 3. The weighted supermatrix is produced by adjusting the unweighted supermatrix so that the sum of the entries in each column is equal to one. In this study, the unweighted and weighted supermatrices are identical.

Step 6: Extracting global weights. To elicit the global weights w_i, the weighted supermatrix is limited by raising it to a sufficiently large power so that it converges into a stable supermatrix (all columns being identical), also called a limiting supermatrix. Table 4 constitutes the limiting supermatrix after the power of 19, showing that the global weights from w1 to w_{10} are 0.077, 0.109, 0.107, 0.107, 0.275, 0.029, 0.025, 0.086, 0.108 and 0.077, respectively, being the results of considering dependences and influences among indicators. Solid waste (I_5), especially referring to construction waste, obtains the highest global weight (0.275) because the production of construction waste implies more TSP, SS, noise, soil pollution, and more destruction of terrestrial and aquatic habitats. However, aquatic (I_7) has the lowest global weight (0.025) due to low influence.

Table 2 Ten sets of derived influence weights and aggregation results

	α_k-cut										Aggregation
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	
$w_{12}(\alpha_k)$	0.018	0.018	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	w_{12}=0.019
$w_{22}(\alpha_k)$	0.679	0.681	0.682	0.683	0.685	0.686	0.686	0.688	0.691	0.691	w_{22}=0.688
$w_{32}(\alpha_k)$	0.114	0.112	0.110	0.109	0.107	0.106	0.106	0.103	0.102	0.102	w_{32}=0.105
$w_{42}(\alpha_k)$	0.018	0.018	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019	w_{42}=0.019
$w_{52}(\alpha_k)$	0.102	0.102	0.101	0.101	0.101	0.101	0.101	0.101	0.100	0.100	w_{52}=0.101
$w_{62}(\alpha_k)$	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	w_{62}=0.010
$w_{72}(\alpha_k)$	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	w_{72}=0.028
$w_{82}(\alpha_k)$	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	w_{82}=0.010
$w_{92}(\alpha_k)$	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	w_{92}=0.010
$w_{102}(\alpha_k)$	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010	w_{102}=0.010
λ_k^*	0.974	0.974	0.974	0.973	0.973	0.972	0.972	0.972	0.971	0.971	

Table 3 Unweighted supermatrix

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}
Air (I_1)	0.736	0.019	0.019	0.010	0.020	0.110	0.089	0.028	0.010	0.010
Water (I_2)	0.019	0.688	0.100	0.010	0.020	0.149	0.249	0.033	0.010	0.010
Soil (I_3)	0.046	0.105	0.491	0.010	0.100	0.130	0.110	0.030	0.010	0.010
Noise (I_4)	0.010	0.019	0.010	0.872	0.010	0.050	0.050	0.028	0.010	0.010
Solid waste (I_5)	0.063	0.101	0.300	0.048	0.771	0.119	0.109	0.030	0.010	0.010
Terrestrial (I_6)	0.010	0.010	0.031	0.010	0.029	0.353	0.010	0.030	0.010	0.010
Aquatic (I_7)	0.010	0.028	0.019	0.010	0.020	0.010	0.304	0.030	0.010	0.010
Economics (I_8)	0.086	0.010	0.010	0.010	0.010	0.010	0.010	0.671	0.069	0.099
Society (I_9)	0.010	0.010	0.010	0.010	0.010	0.059	0.059	0.060	0.788	0.099
Culture (I_{10})	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.060	0.073	0.732

Table 4 Limiting supermatrix

	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}
Air (I_1)	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077
Water (I_2)	0.109	0.109	0.109	0.109	0.109	0.109	0.109	0.109	0.109	0.109
Soil (I_3)	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107
Noise (I_4)	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107	0.107
Solid waste (I_5)	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275	0.275
Terrestrial (I_6)	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029	0.029
Aquatic (I_7)	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025	0.025
Economics (I_8)	0.086	0.086	0.086	0.086	0.086	0.086	0.086	0.086	0.086	0.086
Society (I_9)	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108	0.108
Culture (I_{10})	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077

Fig. 5 Route of Taiwan High-Speed Rail project

Step 7: Synthesis. The final score ϕ of the environmental impact evaluation is computed by a weighted summation and formulated as

$$\phi = \sum_{i=1}^{n} w_i \phi_i \tag{3}$$

where n is the number of indicators.

3. Application to Taiwan High-Speed Rail POroject)

3.1 Case Description

Taiwan, located 160-km southeast of Mainland China, is in a subtropical island with beautiful and splendid natural scenery. Its total area is 35,961 km^2, more than 70% of which is mountainous terrain, more than half having an altitude above 1000 meters. The population is 21.3 million, 95% of which inhabits the Western Corridor. The major metropolises are Taipei in the north, with a population of 6.15 million, and Kaoshiung in the south, with a population of 2.71 million. Other cities along the Western Corridor are Taoyuan, Hsinchu, Taichung and Tainan. In 1987, in view of the deteriorating quality and saturation of transportation in the Western Corridor, the Taiwan Transportation Bureau was appointed by the Executive Yuan to undertake a 'Feasibility Study for a High-Speed Rail System in the Western Corridor.' The aim of this study was to improve the transportation service in this area and coordinate with the metropolitan rapid transport system plan for constructing a complete transportation network.

After almost 13 years of preparation and planning, the construction work on the Taiwan High-Speed Rail (THSR) system began on March 27, 2000. The THSR project, the route of which is mapped in Fig. 5, is not only one of the most challenging infrastructure projects in the world to date but also the largest private-sector-invested public construction project concurrently. The total construction investment needed is approximately USD 15 billion. The planned system is 344.68 kms in length, including 252 kms of overpasses and 48 kms of tunnels, for which revenue service is projected to commence by the end of 2006. The THSR line runs from Taipei to Kaohsiung, passing 14 major cities and counties and 77 townships and regions. In the earliest phase, eight stations located in Taipei, Banciao, Taoyuan, Hsinchu, Taichung, Chiayi, Tainan and Kaohsiung, will be operational. Four additional stations (Nangang, Miaoli, Changhua, and Yunlin Stations) will be built in a later phase.

For preventing a lateral impact on the adjacent environment along the THSR line within the construction and operation stages, the Taiwan Transportation Bureau conducted an environmental impact assessment report concerning the natural, biological, social and economical impacts, including 20 subjects within the years from 1990 to 1994. The Environmental

Protection Administration of the Executive Yuan approved this EIA report on September 12, 1994. According to the information provided in this EIA report, the integrated evaluation framework consisting of FANP and fuzzy logic demonstrates its use.

Table 5 Fuzzy inference of acceptability of air pollution

Subindicator (Unit)	CO (ppm)	SO_2 (ppb)	NO_2 (ppb)	TSP (ppb)	Acceptability (0-100)
ST	35.0†	250.0†	250.0†	250.0‡	60.0
	Northern section				
BC	5.6	9.1	31.8	199.3	80.7
PIWOM	5.6	9.1	31.8	277.7	77.7
PIWM	5.6	9.1	31.8	230.7	80.3
	Central section				
BC	5.0	14.0	35.4	174.5	80.8
PIWOM	5.0	14.0	35.4	257.1	79.8
PIWM	5.0	14.0	35.4	207.6	80.3
	Southern section				
BC	5.8	7.0	38.8	271.4	78.2
PIWOM	5.8	7.0	38.8	340.2	76.4
PIWM	5.8	7.0	38.8	298.9	76.7

Note: ST: standard; BC: baseline condition;
PIWOM: prediction of impact without mitigation measures;
PIWM: prediction of impact with mitigation measures;
†: 1-hour average value; ‡: 24-hour average value

3.2 Evaluation Results

The following sections discuss assessment of the acceptability for each indicator through fuzzy logic and evaluation of the overall environmental impact by the FANP. Both are restricted to the construction phase of the THSR.

(1) Fuzzy Inference of Acceptabilities for Indicators

In this study, the THSR line was divided into three sections: northern, from Taipei to Hsinchu, about 90 kms; central, from Hsinchu to Yunlin, about 130 kms; and southern, from Yunlin to Kaohsiung, about 125 kms. For each THSR section, three conditions are discussed: the baseline condition (BC) before the construction of the THSR, prediction of the impact without mitigation measures (PIWOM) and prediction of the impact with mitigation measures (PIWM), as shown in Tables 5 and 6.

First, fuzzy reasoning for the acceptability of air pollution is illustrated. The 81 fuzzy rules for evaluating air quality produced in section 2.1 are triggered by measured and predicted concentrations of air pollutants in the EIA report, the results of which are presented in Table 5. The concentrations listed in the four middle columns in Table 5 represent the average values over all measurement points within the respective sections. The acceptability of the air-quality standard is presumed to be 60%, the minimally acceptable value. This assumption is also applicable to the standard values of other subindicators when available. For the baseline condition, with the exception of total suspended particulates (TSP), the other air pollutants (CO, SO_2 and NO_2) were far below the air-quality standard, thereby inducing the acceptabilities of 80.7%, 80.3% and 78.2% in the northern, central and southern sections, respectively. The concentrations of CO, SO_2 and NO_2 were predicted not to cause increases in the construction phase of the THSR; however, a large amount of dust could be generated due to ground excavations, handling materials, truck haulage on unpaved site roads, as well as construction of stations, bridges, and tunnels. The exceedances of TSP for a 24-hour average were predicted at 100 air-sensitive receivers, thereby causing a decline in acceptabilities, i.e., 77.7%, 79.8% and 76.4% in the northern, central and southern sections, respectively. The number of air-sensitive receivers could be reduced to 54 and the increments of TSP concentrations eliminated by 60% by performing certain mitigation measures, such as spraying water to keep the hauling roads in a wet condition, reducing vehicle speeds and limiting vehicular movements in unpaved areas, providing wheel- and body-washing facilities at exits from the site, cleaning public roads wherever necessary, and covering all dusty vehicle loads with tarpaulins for transportation to, from and between site locations. With these mitigation measures, the acceptabilities improved to 80.3%, 80.3% and 76.7% in the northern, central and southern sections, respectively. In contrast with air pollution, water pollution obtains much lower acceptabilities in all conditions via the reasoning of the 27 fuzzy rules formulated in section 2.1 mainly because this pollution was severe at the time of testing (see Table 6). I.e., 40% of the rivers that the THSR would cross were severely polluted; 32%, moderately polluted; 16%, slightly polluted; whereas, only 12% were acceptable.

Table 6 Fuzzy inference of acceptability of water pollution

Subindicator (Unit)	DO (mg/l)	BOD_5 (mg/l)	SS (mg/l)	NH_3-N (mg/l)	Acceptability (0-100)
ST	6.5	3.0	20	0.5	60.0
	Northern section				
BC	5.3	13.9	33.2	4.4	31.6
PIWOM	5.3	13.9	39.3	4.4	30.1
PIWM	5.3	13.9	35.6	4.4	31.1
	Central section				
BC	6.6	31.1	76.5	1.2	29.3
PIWOM	6.6	31.1	105.8	1.2	23.8
PIWM	6.6	31.1	88.2	1.2	24.8
	Southern section				
BC	3.0	14.4	37.7	5.3	28.7
PIWOM	3.0	14.4	42.8	5.3	26.9
PIWM	3.0	14.4	39.8	5.3	28.0

Note: ST: standard; BC: baseline condition;
PIWOM: prediction of impact without mitigation measures;
PIWM: prediction of impact with mitigation measures;

Table 7 Evaluation results

Indicator (weight)	I_1 0.077	I_2 0.109	I_3 0.107	I_4 0.107	I_5 0.275	I_6 0.029	I_7 0.025	I_8 0.086	I_9 0.108	I_{10} 0.077	EIE (acceptability)
	Northern section										
BC	80.7	31.6	82.2	65.8	70.2	77.0	56.2	71.0	68.2	72.8	67.51
PIWOM	77.7	30.1	80.9	56.6	29.2	52.5	53.1	61.9	65.4	61.8	52.00
PIWM	80.3	31.1	81.7	59.6	63.6	59.3	54.7	63.4	66.3	63.3	62.67
	Central section										
BC	80.8	29.3	82.2	66.1	70.9	77.0	53.5	67.8	64.4	73.0	66.76
PIWOM	79.8	23.8	80.9	57.2	26.8	55.4	51.0	63.4	62.5	60.4	50.62
PIWM	80.3	24.8	81.7	59.6	65.7	61.0	52.5	64.1	63.2	61.8	62.25
	Southern section										
BC	78.2	28.7	82.2	65.9	71.4	77.0	54.8	67.0	63.2	73.2	66.46
PIWOM	76.4	26.9	80.9	57.3	55.9	58.6	52.7	62.4	61.2	60.6	58.63
PIWM	76.7	28.0	81.7	59.9	66.8	66.7	53.7	63.9	61.9	61.9	62.70
	Entire line										
BC	79.8	29.7	82.2	65.9	70.9	77.0	54.7	68.3	65.0	73.0	66.85
PIWOM	78.0	26.6	80.9	57.1	38.0	55.8	52.2	62.6	62.8	60.8	53.88
PIWM	79.0	27.6	81.7	59.7	65.6	62.6	53.5	63.8	63.5	62.2	62.55

Note: ST: standard; BC: baseline condition; PIWOM: prediction of impact without mitigation measures;
PIWM: prediction of impact with mitigation measures.

(2) Overall Eevaluation via FANP

The acceptabilities for the other eight indicators are also inferred through respective sets of fuzzy rules. Table 7 (middle 10 columns) shows the outcomes of fuzzy reasoning. In the northern section, water (I_2), noise (I_4), terrestrial (I_6) and aquatic (I_7) did not reach minimum acceptance, even when the mitigation measures were performed. In central section, water (I_2), noise (I_4) and aquatic (I_7) were below minimum acceptance, despite the application of certain mitigation measures. The southern section had results similar to those of the central section except for much less construction waste. Moreover, the consequences of the entire line sums weighted the inferred conclusions for the three sections in light of the rail-length proportion. It should be noted that a comprehensive plan for construction-waste management, including 29 landfills, can successfully solve the problem of 18.62 million m^3 and transform the unacceptable PIWOM situation into an acceptable PIWM condition.

Finally, the overall evaluation results of the FANP are shown in the last column in Table 7. In the construction phase without mitigation measures, the acceptabilities are all below the minimum, ranging from 50.62 to 58.63; however, these values can be increased to above-minimum acceptance if the mitigation measures are invoked.

4. Conclusion

A framework considering air, water, soil, noise, solid waste, terrestrial, aquatic, economics, society and culture has been developed to evaluate environmental impacts of construction projects during the construction phase. The entire evaluation-framework is composed of the fuzzy analytic network process and fuzzy logic, providing the following benefits:

- Enabled to handle dependence problems among environmental factors through the FANP to derive their relative influences (i.e., global weights);
- Empowered with subjective assessment modeled by fuzzy logic to bridge the gap between scientific measurement and the fulfilment of social values and beliefs;
- Equipped with expressive power via the flexible extension of pairwise comparison to fuzzy judgments.

Although the proposed approach has been demonstrated by a case study of the Taiwan High-Speed Rail project, further investigation is needed in the future, including a refinement of fuzzy rules to reflect realistic situations and the involvement of additional specialists to discuss the dependences among environmental factors.

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