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Decision-support for environmental impact assessment: A hybrid approach using fuzzy logic and fuzzy analytic network process

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ABSTRACT

The decision-making on approval of environmental impact assessment (EIA) is an intrinsically complex multi-dimensional process because it does not only consider the scientific facts but also reflect subjective values. The use of decision-support methods to balance facts and values can be beneficial for decision makers. This paper attempts to propose an integrated decision-support framework that employs fuzzy logic (FL) to manipulate the subjectivity as decision makers do in appraising the facts and values, significance-acceptability transformation (SAT) to incorporate standards and decision makers' risk attitude into decision-making process, and fuzzy analytic network process (FANP) to manage the dependences among environmental factors and suggest an overall acceptability of the proposal. Finally, the proposed approach will be applied to the EIAs of construction projects, exemplified in a case study of the Taiwan High-Speed Rail project.

1. Introduction

Environmental impact assessment (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 (Canter, 1996). The EIA process essentially involves scoping, studying baseline conditions, identifying potential impacts, predicting significant impacts, and evaluating them (Shepard, 2005). 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's significance on environmental effects. Eventually, decision makers (EIA review committee) have to decide whether to accept the proposal or not.

The decision-making on approval of EIA reports is an intrinsically complex multi-dimensional process because it does not only consider the scientific facts (environmental, ecological and socio-economic impacts) but also reflect subjective values (judgment, preference, value and concern). Fig. 1 delineates a flowchart of EIA process; wherein, the use of decision-support methods to balance facts and values can be beneficial for decision makers. Several decision-support methods have been proposed in literature. Among them, two categories are noteworthy. The utilization of analytic hierarchy process (AHP) (Saaty, 1990) and its variants have become the first remarkable category due to their capability for facilitating multi-criteria decision-making. For example, Tsamboulas and Mikroudis (2000) 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, Koh, and Nee (2001) 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, Sólnes (2003) applied the AHP to calculate the environmental quality index of each. Readers are referred to Ramanathan's (2001) discussion on the advantages and shortcomings of using the AHP for environmental impact assessment. Tesfamariam and Sadiq (2006) applied fuzzy AHP to deal with the selection of drilling fluid/mud for offshore oil and gas operations, which incorporated decision maker's risk attitude and associated confidence on the estimates of pairwise comparisons. Srdjevic (2007) proposed a methodology for combining multi-criteria decision-making and social choice theory in a group decision-making process and used it to select the most

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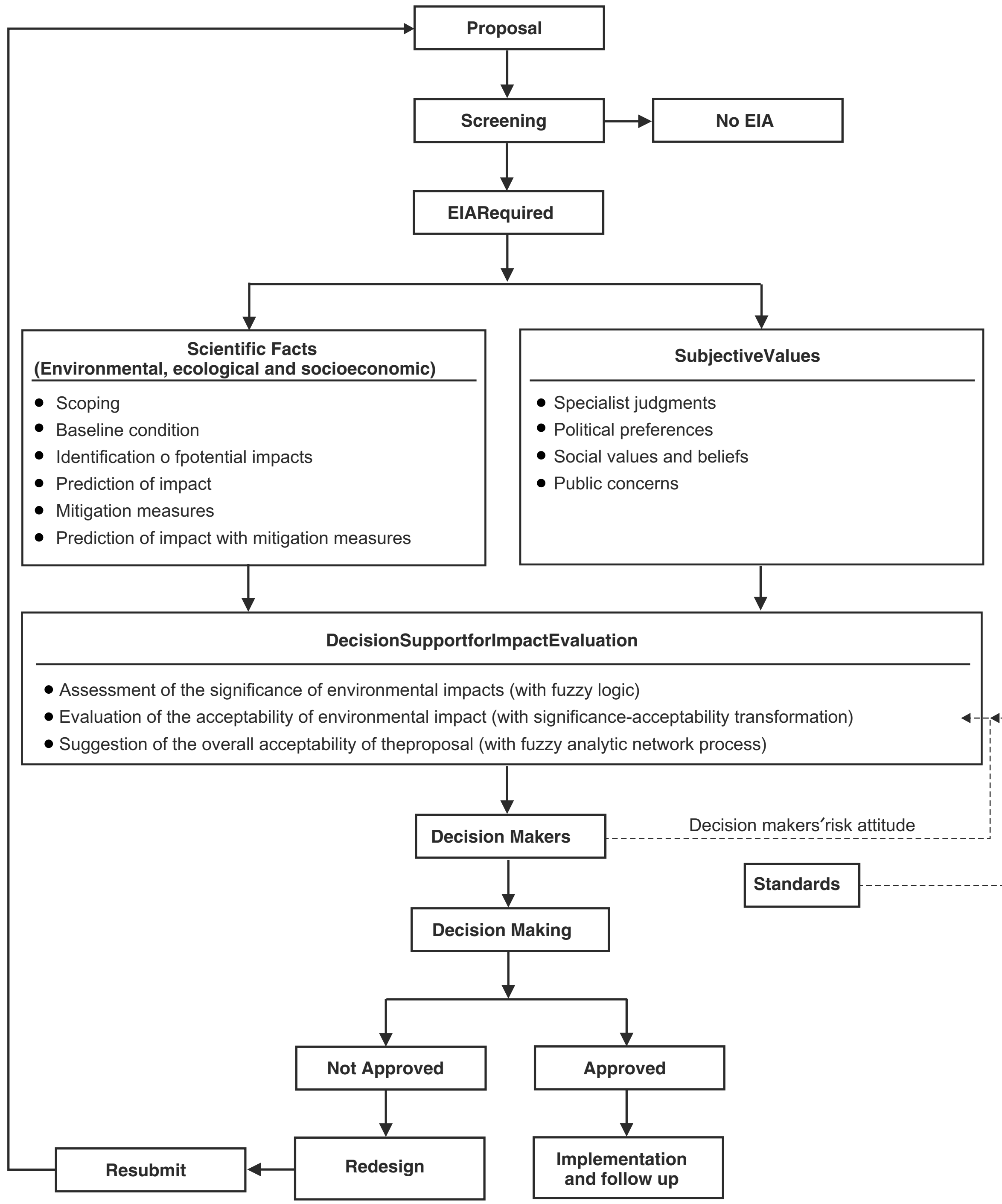

Fig. 1. A decision-making process for environmental impact assessment.

desired long-term water management plan. Brent, Rogers, Ramabitsa-Siimane, and Rohwer (2007) focused on the application of the AHP technique in the context of sustainable development to establish and optimise health care waste management systems in rural areas of developing countries. Liu (2007) outlines a new integration of fuzzy logic and fuzzy AHP to perform the evaluation of environmental sustainability in 146 countries. The analytic network process (ANP) (Saaty, 2001) 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, Gregory, O'Neill, and Smith (2004) conducted an integrated environmental assessment by combining principal component analysis and the ANP. Cheng and Li (2005) 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 (2003) 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.

The second category exploits the fuzzy logic method to inference the environmental impacts or significances. For instance, Borri, Concilio, and Conte (1998) 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 (1998), as well as Roussel, Cavelier, and Van der Werf (2000), 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. Marusich and Wilkinson (2001) conducted two EIA cases with fuzzy logic and concluded that fuzzy logic analysis can make a valuable contribution to the environmental assessment of complex projects but it offers no significant benefits in the case of simple projects. González, Adenso-Díaz, and González-Torre (2002) 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. Siqueira Campos Boclin and Mello (2006) used a fuzzy logic computational approach to operating fuzzy and crisp variables and make inferences from resultant values of the systemic indicator as well as environmental, cultural, social and economic thematic indicators.

After investigating these relevant papers, we summarize three 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*: Three sources of subjectivity in EIA originate in estimating the relative importances of environmental factors, evaluating the impacts induced by a project and incorporating decision makers' risk attitude (tolerance). All 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 (2000) stated: 'The influence of personal value systems and beliefs is unavoidable when creating an expert evaluation and interpretation (p. 431).'
- *Imprecision accompanied by subjectivity*: Imprecision arises 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.

To consider these three properties of EIA simultaneously, this study attempted to propose an integrated decision-support framework that combines fuzzy logic and fuzzy analytic network process to help decision makers in EIA. Furthermore, this framework also consider decision makers' risk attitude. More specifically, this study sought to fulfil environmental impact evaluations in terms of the following decision support methods (see Fig. 1):

- fuzzy set theory to model the imprecision of the subjectivity,
- fuzzy logic (FL) to manipulate the subjectivity as decision makers do in balancing the facts and values,
- significance-acceptability transformation (SAT) to incorporate standards and decision makers' risk attitude into decision-making process, and
- fuzzy analytic network process (FANP) to manage the dependences among environmental factors and suggest an overall acceptability of the proposal.

The details of this framework is discussed in Section 2. Finally, the proposed approach was applied to the EIAs of construction projects, exemplified in a case study of the Taiwan High-Speed Rail project.

2. Decision-support methodologies

2.1. Overall decision-support framework

An integrated decision-support framework for EIA of public infrastructure projects during construction is depicted in Fig. 2. This framework considers the overall acceptability of a proposal 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) and solid waste (I_5); the ecological alteration contains two indicators: terrestrial (I_6) and 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 'significance' of an environmental impact is adopted from previous literature (Canter & Canty, 1993; Cloquell-Ballester, Monterde-Diaz, Cloquell-Ballester, & Santamarina-Siurana, 2007; Duinker & Beanlands, 1986; Dzidzornu, 2001). Significance is a complex concept that relates not only to impact magnitude but also to other considerations such as effects upon environmental, ecological and socioeconomic aspects. Thus, determining the significance of environmental impacts may be viewed as highly subjective judgment because it has to ruminate over the science facts and societal values. As shown in the part (a) of Fig. 2, the fuzzy logic is applied to infer the significances because it can imitate human thinking process. The level of significance is represented as a score ranging from 0 (i.e., insignificant) to 100 (i.e., completely significant). The significance determination of impacts related to these indicators is based on their respective subindicators. 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 significances of the indicators is outlined in Section 2.2.

Acceptability is another core concept of EIA, which is more abstract than significance (Shepard, 2005). In this paper, the degree of acceptability is depicted as a score ranging from 0 (i.e., unacceptable) to 100 (i.e., completely acceptable). The second part of the framework is to transform the impact significance into the acceptability (see the part (b) of Fig. 2). The acceptability of an indicator is not only derived from its significance but also relevant standards and decision makers' risk attitude. Standards will be jurisdiction specific and provide an objective, technical means of determining acceptability; decision makers' risk

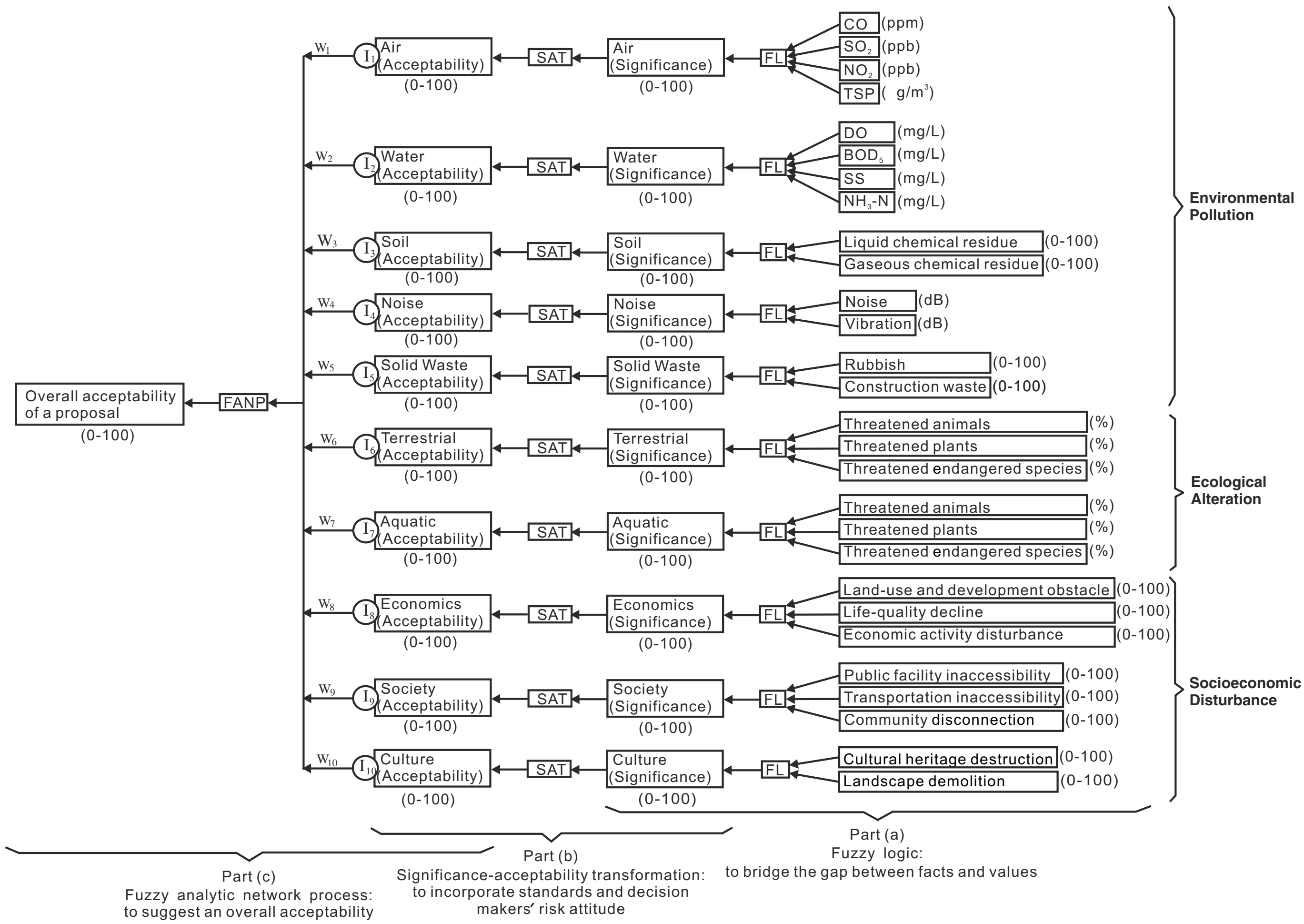

Fig. 2. An integrated decision-support framework for EIA of public infrastructure projects during construction.

attitude reflect the confidence on the estimates of significances. The significance-acceptability transformation (SAT) is described in Section 2.3.

The third part of the framework is to provide decision makers the overall acceptability of a proposal. While the assessments of the significance and acceptability for each single environmental factor is informative, the suggestion of the overall acceptability of a proposal can be of value to decision makers. 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 utilized the fuzzy analytic network process (Mikhailov & Madan, 2003) to evaluate the environmental impact on the basis of the ten indicators shown in the part (c) of Fig. 2 and discussed in 2.4.

2.2. Fuzzy logic: to bridge the gap between facts and values

Fuzzy logic (Zadeh, 1996) 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 significance 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 *significance of I_1 is very strong*.
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 *significance of I_1 is strong*.
⋮ ⋮
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 *significance of I_1 is weak*.
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 *significance of I_1 is very weak*.

where '*CO concentration*,' 'SO_2 *concentration*,' 'NO_2 *concentration*,' '*TSP concentration*' and '*strong of* I_1' are linguistic variables; '*high*,' '*medium*,' '*low*,' '*very strong*,' '*strong*,' '*weak*' and '*very weak*' are their possible fuzzy values, as defined by membership functions in fuzzy set theory (as shown in Fig. 3).

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* 199.3 $\mu g/m^3$) are fed into this inference mechanism, fuzzy reasoning (Zadeh, 1975) proceeds. The theory of fuzzy reasoning is detailed in Appendix A and it can be easily explained by a graphical representation as shown in Fig. 4. In this figure, four major steps in reaching a conclusion using fuzzy reasoning are described as follows:

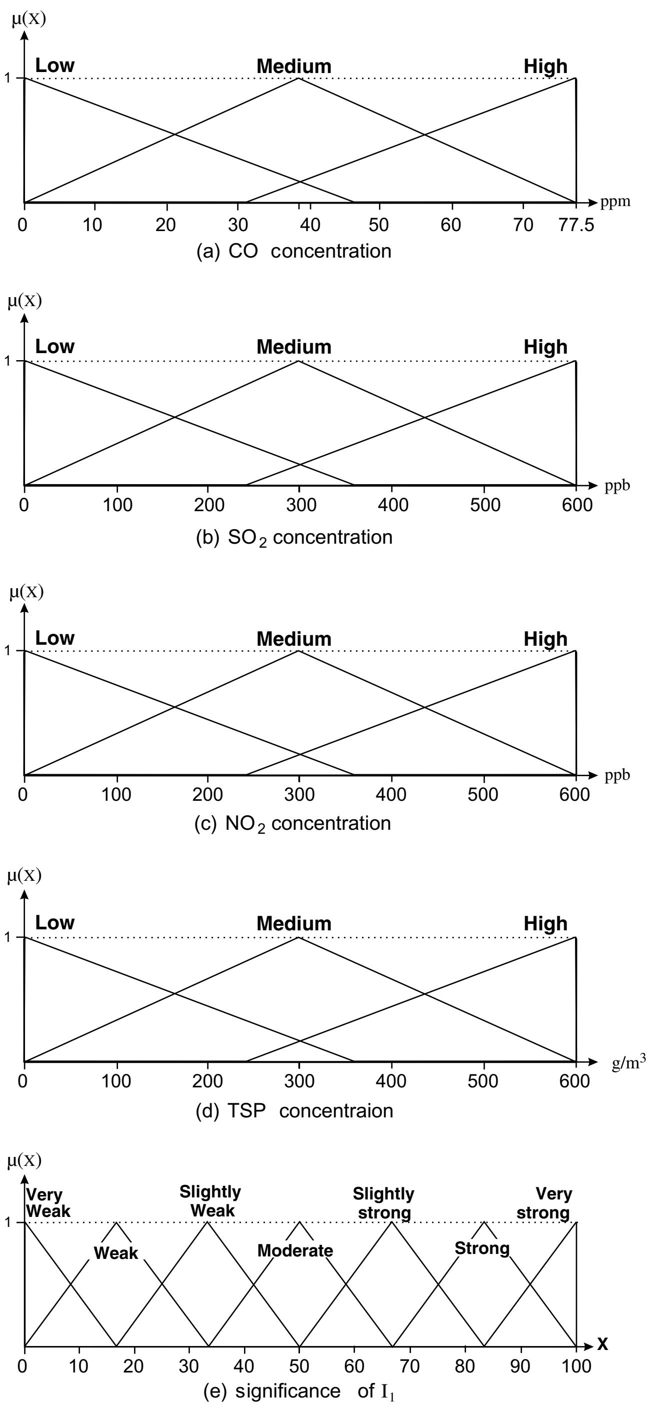

Fig. 3. Membership functions of fuzzy values for linguistic variables (a) CO concentration, (b) SO_2 concentration, (c) NO_2 concentration, (d) TSP concentration and (e) significance of I_1.

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 0.888; for Fact 2 with 'SO_2 *concentration is low*,' 0.975; for Fact 3 with 'NO_2 *concentration is low*,' 0.912; for Fact 4 with '*TSP concentration is medium*,' 0.664. It should be noted that 'product' is chosen as the *t*-norm operator instead of another more widely used *t*-norm operator, 'min,' because the *t*-norm operator 'product' makes the conclusion sensitive to every input; whereas, only one input will control the conclusion in the case of the *t*-norm operator 'min.' The overall compatibility of Rule 80 with the four facts is computed by $0.888 \cdot 0.975 \cdot 0.912 \cdot 0.664$, thereby obtaining 0.524. Similarly, the compatibilities of Rules 81 with the same facts are 0.352. The compatibilities of other rules are also calculated in the same way.

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. 4, a trapezoid conclusion is then inferred by truncating the triangular conclusion of each rule with its corresponding compatibility. The use of implication operator 'min' results in the truncations of each conclusion; whereas, a conclusion will be scaled if the implication operator 'product' is selected.

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. 4, the final conclusion is aggregated by using the union of all truncated conclusions.

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 utilized 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. 4 indicates that the score of significance for air pollution is 18.0.

For evaluating the significances of the ten indicators, 10 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. These 10 rule-bases and their corresponding fuzzy inference systems are implemented with MATLAB Fuzzy Logic Toolbox.

2.3. Significance-acceptability transformation (SAT): to incorporate standards and decision makers' risk attitude

Although it is intuitive to consider that impact significance and acceptability are the contrary notions, relevant standards and decision makers' risk attitude still have key roles in determining the acceptability of a impact in the light of its significance appraisal. The first portion of SAT is to incorporate the standards into SAT. An assumption is that each subindicator has a standard value when evaluating significance. Air, water or noise-quality standards have no difficulty in such assumption; however, an appropriate technical standard for other subindicators will not be available, especially for ecological, social and economic impacts. This study utilized

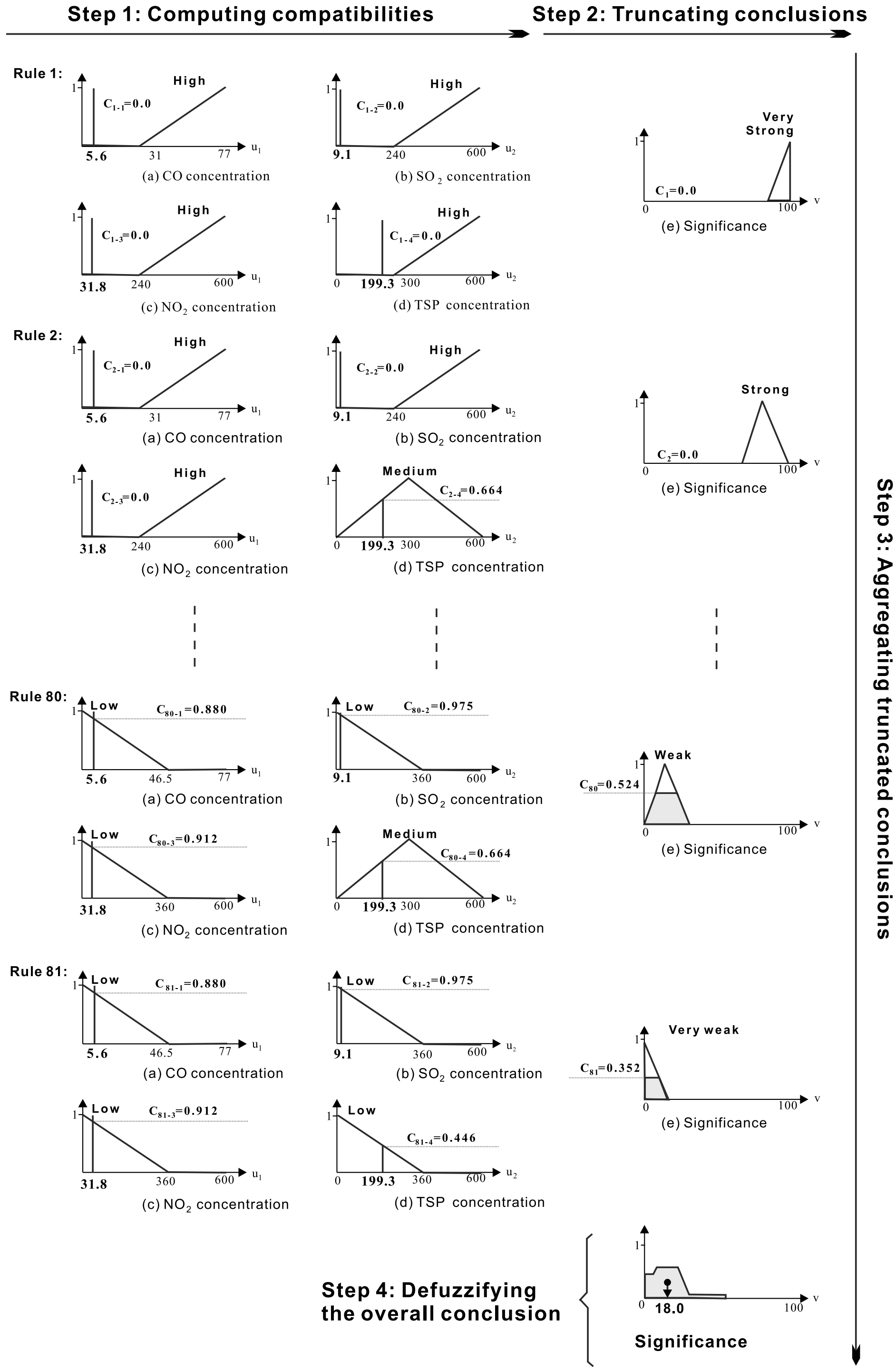

Fig. 4. Graphical representation of fuzzy reasoning.

human experts to calibrate standard values for those subindicators which do not have regulatory standards. All standard values for these subindicators are listed in the right part of Table 1; the associated significances for 10 indicators inferred by fuzzy logic are represented in the left part of which. For all indicators, the lower bound (i.e., 0) of significance is designated to correspond to the upper bound (i.e., 100) of acceptability; on the contrary, the upper bound (i.e., 100) of significance corresponds to the lower bound (i.e., 0) of acceptability; most of all, the significance values of standards keep to the acceptability score, 60. The first portion of SAT which incorporates the standards is formulated as

$$ac'_i = \begin{cases} 100 - 40\frac{si_i}{sd_i}, & si_i \leqslant sd_i, \\ 60 - 60\frac{si_i - sd_i}{100 - sd_i}, & si_i \geqslant sd_i, \end{cases} \tag{1}$$

where ac'_i is the level of acceptability for indicator I_i, si_i is the significance value inferred by fuzzy logic for I_i and sd_i is the significance value of standards for I_i. Eq. (1) is also illustrated in Fig. 5a.

The second portion of SAT is undertaken by including the decision makers' risk attitude into SAT. The confidence of decision makers on the estimates of significances denoted as the risk index (ri), which is defined as

Table 1
Significances of standards through fuzzy logic

Indicator (I_i)	Significance of I_i	Subindicator	Standard value	Unit
Air (I_1)	45.0	CO	35.0	ppm
		SO_2	250.0	ppb
		NO_2	250.0	ppb
		TSP	250.0	μg/m^2
Water (I_2)	28.3	DO	6.5	mg/L
		BOD_5	3.0	mg/L
		SS	20.0	mg/L
		NH_3–N	0.5	mg/L
Soil (I_3)	28.5	Liquid chemical residue	20.0	0–100
		Gaseous chemical residue	20.0	0–100
Noise (I_4)	33.0	Noise	70.0	dB
		Vibration	55.0	dB
Solid waste (I_5)	37.9	Rubbish	20.0	0–100
		Construction waste	20.0	0–100
Terrestrial (I_6)	19.8	Threatened terrestrial animals	20.0	%
		Threatened terrestrial plants	30.0	%
		Threatened endangered terrestrial species	5.0	%
Aquatic (I_7)	19.8	Threatened terrestrial animals	20.0	%
		Threatened terrestrial plants	30.0	%
		Threatened endangered terrestrial species	5.0	%
Economics (I_8)	24.7	Land-use and development obstacle	20.0	0–100
		Life-quality decline	20.0	0–100
		Economic activity disturbance	20.0	0–100
Society (I_9)	24.7	Public facility inaccessibility	20.0	0–100
		Transportation inaccessibility	20.0	0–100
		Community disconnection	20.0	0–100
Culture (I_{10})	28.5	Cultural heritage destruction	20.0	0–100
		Landscape demolition	20.0	0–100

$$ac_i = 100\left(\frac{ac'_i}{100}\right)^{ri} \tag{2}$$

where ac_i is the final acceptability for I_i, ac'_i is the level of acceptability for I_i and ri is the risk index. When ri is 1, it is a neutral situation; the larger ri, the more pessimistic risk attitude; adversely, the smaller ri, the more optimistic risk attitude. Eq. (2) is also illustrated in Fig. 5b. The decision makers' risk attitude is roughly categorized as 'very optimistic,' 'optimistic,' 'slightly optimistic,' 'neutral,' 'slightly pessimistic,' 'pessimistic' and 'very pessimistic,' which are characterized by risk indexes 0.63, 0.71, 0.83, 1, 1.2, 1.4 and 1.6, respectively. For example, the value 0.63 of ri can be termed as 'very optimistic risk attitude' which elevates acceptability 60 to 72.5; whereas, the value 1.6 of ri can be labeled as 'very pessimistic risk attitude' which declines acceptability 60 to 44.2. Eqs. (1) and (2) can be consolidated as

$$ac_i = \begin{cases} 100\left(1 - 0.4\frac{si_i}{sd_i}\right)^{ra}, & si_i \leqslant sd_i, \\ 100\left(0.6 - 0.6\frac{si_i - sd_i}{100 - sd_i}\right)^{ra}, & si_i \geqslant sd_i. \end{cases} \tag{3}$$

The illustrations of SAT for significance of standard = 30, 40, 50 and 60 are displayed from Fig. 5c to f, respectively.

2.4. Fuzzy analytic network process: to suggest an overall acceptability

The analytic hierarchy process (AHP) (Saaty, 1990) is a notable multi-criteria decision-making tool, which assumes that a decision-making problem can be continuously decomposed into a multi-leveled hierarchy, where the elements in each level are independent from each other. The AHP can help decision-makers prioritize the alternatives on a pairwise comparison basis. The analytic network process (ANP) (Saaty, 2001) 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) (Mikhailov & Madan, 2003) has been developed to tolerate fuzzy judgments in a pairwise comparison process, which can be summarized in seven steps (see Fig. 6).

Step 1: Developing a decision hierarchy. A hierarchical structure including the decision goal, clusters, criteria, subcriteria and lower elements is configured. In Fig. 6, the goal 'overall acceptability of a proposal' is decomposed into three clusters (environmental pollution, ecological alteration and socioeconomic disturbance) and the acceptabilities of ten indicators (air (I_1), water (I_2), soil (I_3), noise (I_4), solid waste (I_5), terrestrial (I_6), aquatic (I_8), 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 overall acceptability 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. 7, 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

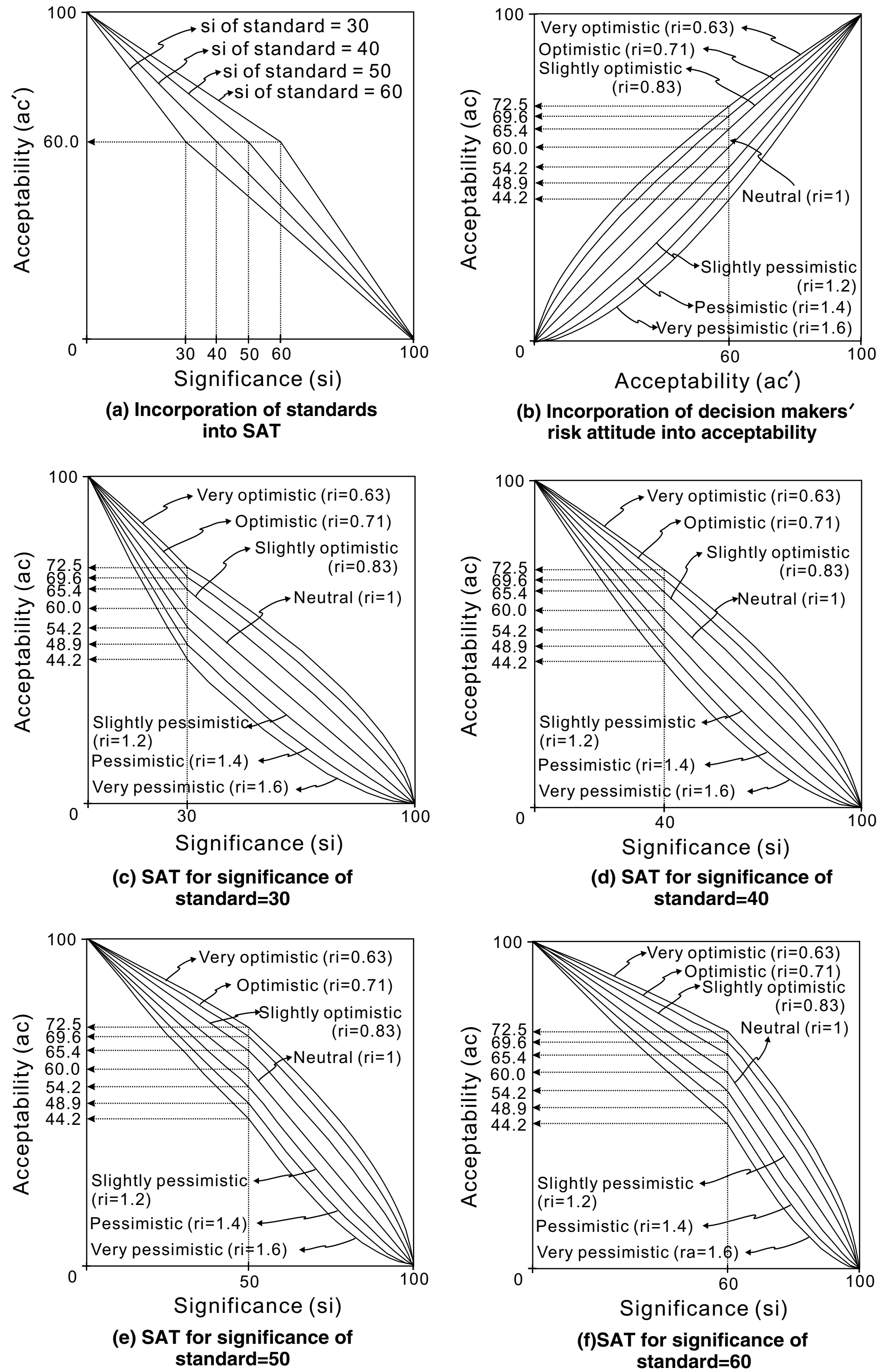

Fig. 5. Significance-acceptability transformation (SAT): (a) incorporation of standards into SAT, (b) incorporation of decision makers' risk attitude into acceptability, (c) SAT for significance of standard = 30, (d) SAT for significance of standard = 40, (e) SAT for significance of standard = 50 and (f) SAT for significance of standard = 60.

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 I_i with respect to water pollution I_2, a fuzzy influence matrix $\widetilde{A}_2$ of pairwise comparison is constructed in Table 1. The entry $\tilde{a}_{ik}$ of $\widetilde{A}_2$, 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, $\tilde{a}_{51}$ is $\tilde{5}$, thereby indicating that the

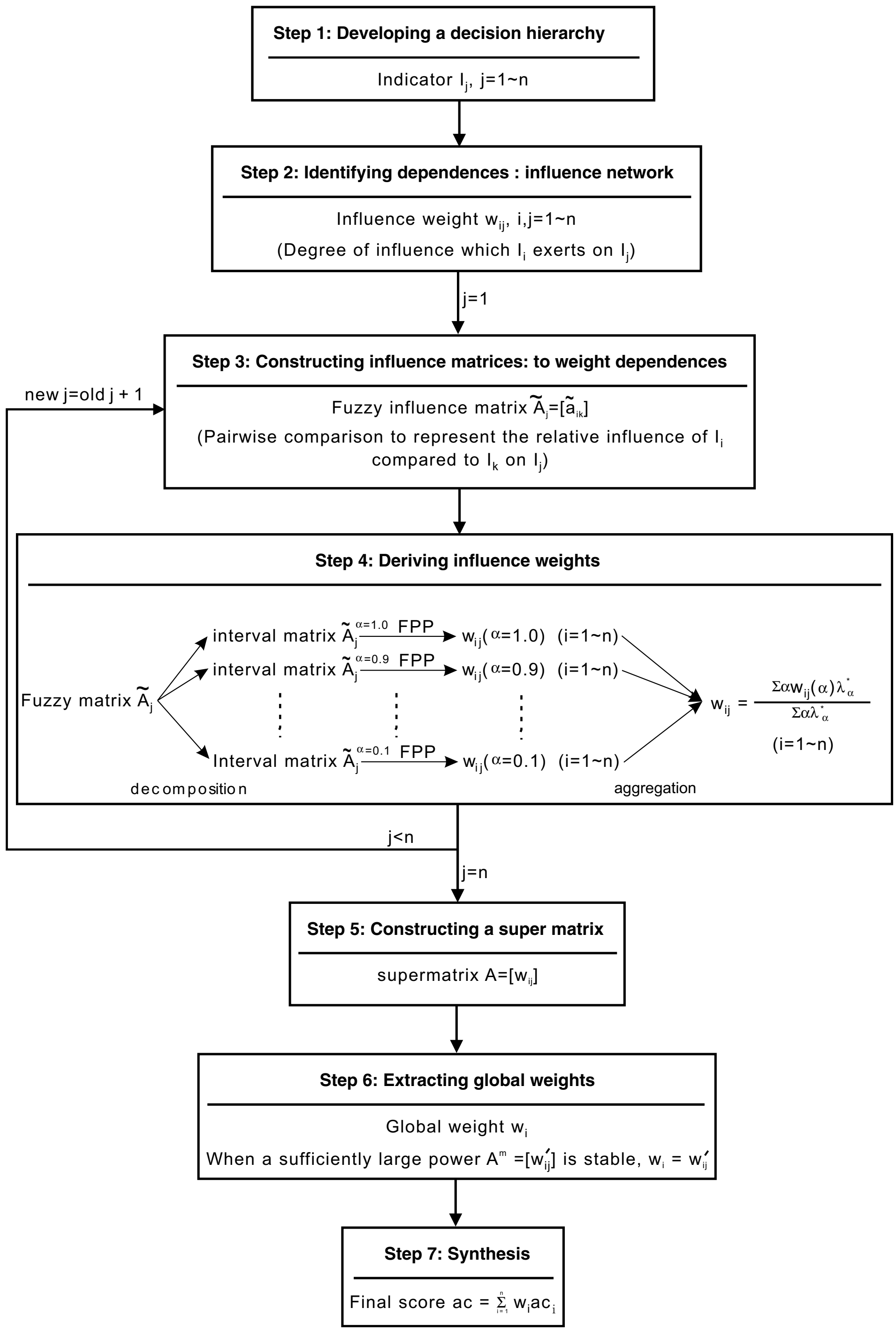

Fig. 6. Seven steps for fuzzy analytic network process.

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 & Madan, 2003) for calculating priorities from fuzzy pairwise comparison judgements is employed to derive influence weights from a fuzzy influence matrix, which is detailed in Appendix B. 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 Eq. (1) as

$$w_{ij} = \frac{\sum \alpha w_{ij}(\alpha)\lambda_\alpha^*}{\sum \alpha\lambda_\alpha^*}, \tag{4}$$

where λ_α^* is the consistency index for influence weights $w_{ij}(\alpha)$. 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.

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 A is produced by adjusting the unweighted supermatrix so that the sum of the entries in each column is equal to one. In this

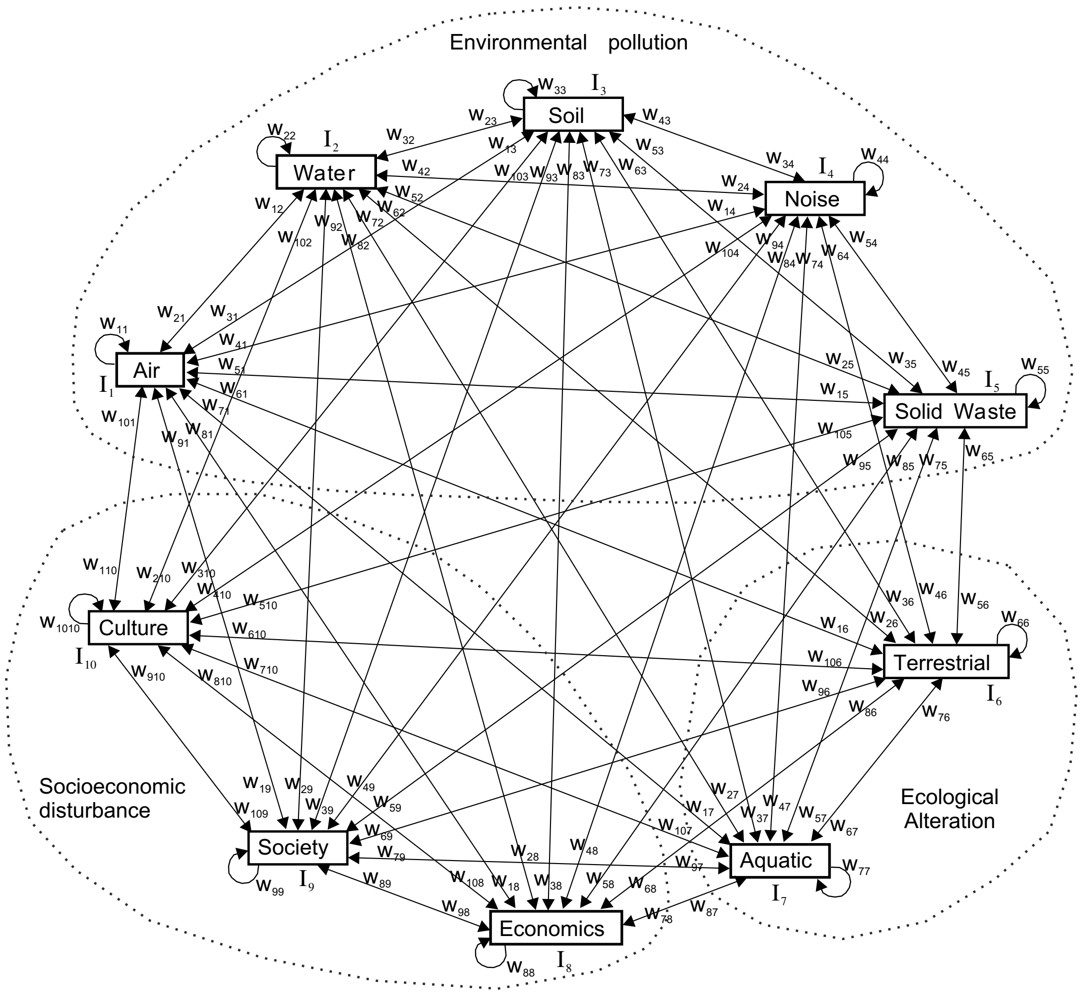

Fig. 7. Influence network.

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

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 w_1 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.

Step 7: Synthesis. The final score *ac* of the overall acceptability is computed by a weighted summation and formulated as

$$ac = \sum_{i=1}^{n} w_i ac_i, \tag{5}$$

where n is the number of indicators.

2.5. Sensitivity analysis

In this paper, sensitivity analysis for the decision-support framework intends to examine the variation of its output (i.e., the score of acceptability) by gradually increasing (or decreasing) its inputs (i.e., the values of the 28 subindicators). Before proceeding to the following discussions, the term ‘deterioration-gradient’ of the inputs of the framework is defined as one-percentage change (i.e., increase or decrease) of scales for all inputs with the same goal of deteriorating the output. In other words, ‘deterioration-gradient’ of the inputs means 1% decrease of scale for inputs in which high values correspond to high levels of output, and 1% increase of scale for other inputs in which low values correspond to high levels of output. As shown in Fig. 8, the output change of the decision-support framework of EIA with respect to ‘deterioration-gradient’ of

Table 3
Ten sets of derived influence weights and the aggregation result

	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 4
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

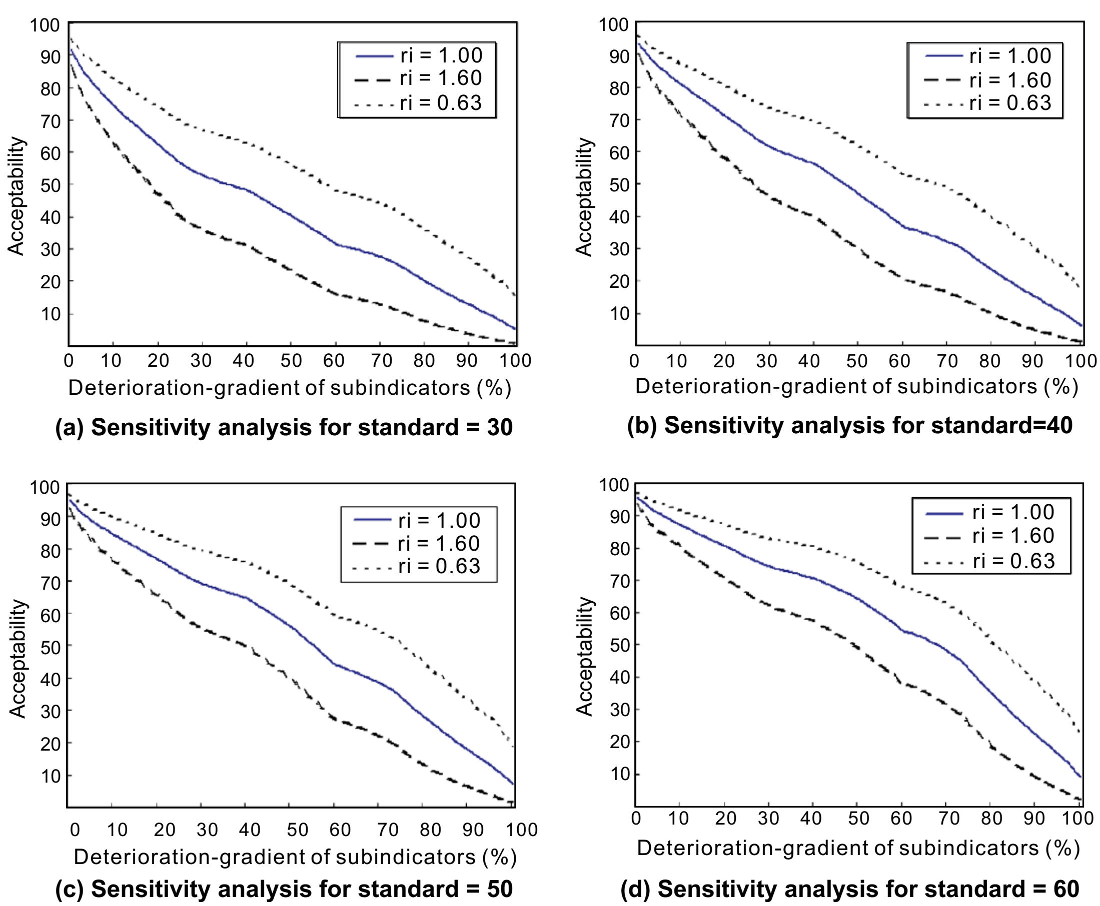

Fig. 8. Sensitivity analysis of the decision-support framework: change of acceptability due to deterioration-gradient of subindicators (a) with significance of standard = 30, (d) with significance of standard = 40, (e) with significance of standard = 50 and (f) with significance of standard = 60.

subindicators is a winding curve, which reflects the non-linearity characteristic of human thinking process.

3. Application to Taiwan High-Speed Rail project

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 m. The population is 23.0 million, 95% of which inhabits the Western Corridor. The major metropolises are Taipei in the north, with a population of 6.15 million, and Kaohsiung 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. 9, 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 km in length, including 252 km of overpasses and 48 km 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 Zuoying, will be operational. Five additional stations (Nangang, Miaoli, Changhua, Yunlin Stations and Kaohsiung) will be built in a later phase.

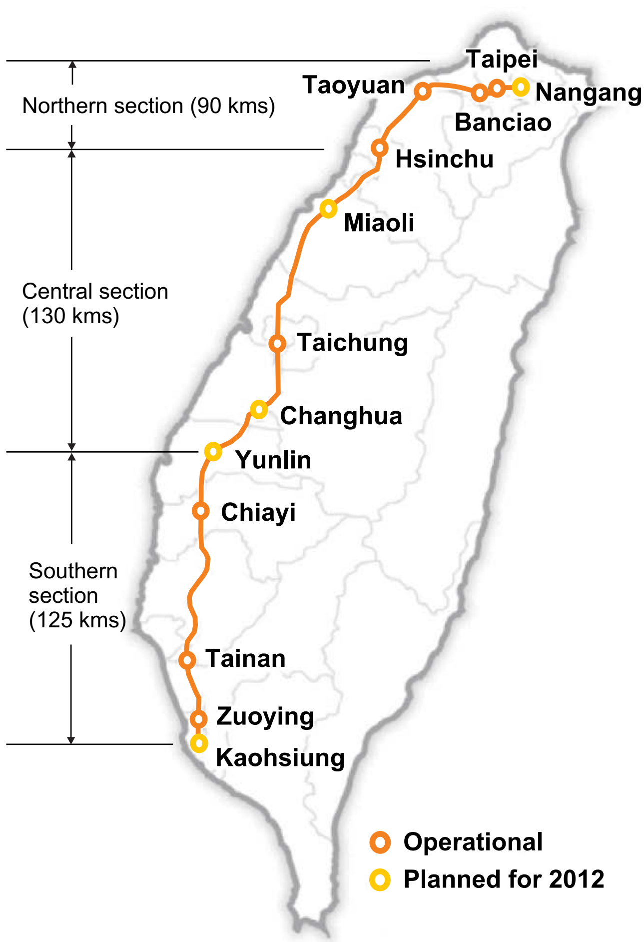

Fig. 9. Route of Taiwan High-Speed Rail project.

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 decision-support framework consisting of fuzzy logic, SAT and FANP demonstrates its use.

3.2. Evaluation results and discussion

The following sections discuss the assessment of the significance for each indicator through fuzzy logic, the fulfillment of significance-acceptability transformation, and the evaluation of the overall acceptability of the project by the FANP. All are restricted to the construction phase of the THSR.

3.2.1. Fuzzy inference of significances for indicators

In this study, the THSR line was divided into three sections (see Fig. 9): northern, from Taipei to Hsinchu, about 90 km; central, from Hsinchu to Yunlin, about 130 km; and southern, from Yunlin to Kaohsiung, about 125 km. 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) (see Table 5).

First, fuzzy reasoning for the significance of air pollution is illustrated. The 81 fuzzy rules for evaluating air impact produced in Section 2.2 are triggered by measured and predicted concentrations of air pollutants in the EIA report, the results of which are presented in Table 6. The concentrations listed in the four middle columns in Table 6 represent the average values over all measurement points within the respective sections. The significance of the air-quality standard is 45.0. 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 significances of 18.0, 17.3 and 19.3 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-h average were predicted at 100 air-sensitive receivers, thereby causing a increase in significances, i.e., 19.4, 18.8 and 19.7 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

Table 5
Liminting 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

Table 6
Fuzzy inference of significance of air pollution

Subindicator (Unit)	CO (ppm)	SO_2 (ppb)	NO_2 (ppb)	TSP (ppb)	Significance (0–100)
ST	35.0[a]	250.0[a]	250.0[a]	250.0[b]	45.0
Northern section					
BC	5.6	9.1	199.3	31.8	18.0
PIWOM	5.6	9.1	277.7	31.8	19.4
PIWM	5.6	9.1	230.7	31.8	18.6
Central section					
BC	5	14	174.5	35.4	17.3
PIWOM	5	14	257.1	35.4	18.8
PIWM	5	14	207.6	35.4	18.0
Southern section					
BC	5.75	7	271.4	38.8	19.3
PIWOM	5.75	7	340.2	38.8	19.7
PIWM	5.75	7	298.9	38.8	19.6

Note: ST: standard; BC: baseline condition; PIWOM: prediction of impact without mitigation measures; PIWM: prediction of impact with mitigation measures.
[a] One-hour average value.
[b] Twenty-four-hour average value.

Table 7
Fuzzy inference of significance of water pollution

Subindicator (Unit)	DO (mg/l)	BOD_5 (mg/l)	SS (mg/l)	NH_3—N (mg/l)	Significance (0–100)
ST	6.5	3.0	20	0.5	28.3
Northern section					
BC	5.3	13.9	33.2	4.4	48.2
PIWOM	5.3	13.9	39.3	4.4	50.7
PIWM	5.3	13.9	35.6	4.4	49.2
Central section					
BC	6.6	31.1	76.5	1.2	63.4
PIWOM	6.6	31.1	105.8	1.2	70.6
PIWM	6.6	31.1	88.2	1.2	67.7
Southern section					
BC	3	14.4	37.7	5.3	58.6
PIWOM	3	14.4	42.8	5.3	60.2
PIWM	3	14.4	39.8	5.3	59.3

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

tarpaulins for transportation to, from and between site locations. With these mitigation measures, the significances improved to 18.6, 18.0 and 19.6 in the northern, central and southern sections, respectively. In contrast with air pollution, water pollution obtains much higher significances in all conditions via the reasoning of the 27 fuzzy rules formulated in Section 2.2 mainly because this pollution was severe at the time of testing (see Table 7). 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 8
Evaluation results of significances

Indicator	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}
ST	45.0	28.3	28.5	33.0	37.9	19.8	19.8	24.7	24.7	28.5
Northern section										
BC	18.0	48.2	11.2	27.8	25.2	10.0	17.8	14.4	15.5	16.3
PIWOM	19.4	50.7	11.7	32.3	74.0	28.0	19.4	22.6	17.2	26.8
PIWM	18.6	49.2	11.4	31.2	33.2	19.1	18.6	21.0	16.6	24.7
Central section										
BC	17.3	63.4	11.2	28.0	24.5	10.0	19.3	16.3	19.3	16.6
PIWOM	18.8	70.6	11.7	31.6	77.4	25.6	20.5	19.8	21.0	28.7
PIWM	18.0	67.7	11.4	30.6	29.7	18.7	19.7	19.0	20.3	26.9
Southern section										
BC	19.3	58.6	11.2	27.9	23.9	10.0	18.8	16.6	22.2	16.7
PIWOM	19.7	60.2	11.7	31.6	46.4	26.3	19.7	20.3	24.3	28.4
PIWM	19.6	59.3	11.4	30.7	28.4	17.5	19.3	19.1	23.5	26.7
Entire line										
BC	18.2	57.7	11.2	27.9	24.5	10.0	18.7	15.9	19.4	16.6
PIWOM	19.3	61.6	11.7	31.8	65.3	26.5	19.9	20.7	21.2	28.1
PIWM	18.7	59.8	11.4	30.8	30.1	18.4	19.3	19.6	20.5	26.3

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

Table 9
SAT results of transforming significances into acceptabilities (with neutral risk attitude)

Indicator	I_1I_2		I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}
ST	60.0	60.0	60.0	60.0	60.0	60.0	60.0	60.0	60.0	60.0
Northern section										
BC	84.0	43.4	84.3	66.3	73.4	79.9	64.0	76.6	75.0	77.1
PIWOM	82.8	41.3	83.7	60.8	25.1	53.9	60.8	63.4	72.1	62.3
PIWM	83.4	42.5	84.0	62.2	65.0	61.3	62.3	66.0	73.1	65.3
Central section										
BC	84.6	30.6	84.3	66.1	74.1	79.9	61.0	73.7	68.7	76.7
PIWOM	83.2	24.6	83.6	61.7	21.8	55.6	59.5	67.9	66.1	59.8
PIWM	84.0	27.0	84.0	62.9	68.7	62.2	60.1	69.2	67.2	62.2
Southern section										
BC	82.8	34.6	84.3	66.2	74.8	79.9	62.0	73.2	64.1	76.5
PIWOM	82.5	33.3	83.6	61.7	51.8	55.1	60.2	67.1	60.7	60.1
PIWM	82.5	34.0	84.0	62.8	70.0	64.6	61.1	69.1	61.9	62.4
Entire line										
BC	83.8	35.4	84.3	66.2	74.2	79.9	62.1	74.3	68.7	76.7
PIWOM	82.8	32.1	83.6	61.5	33.5	55.0	60.1	66.5	65.7	60.5
PIWM	83.3	33.6	84.0	62.7	68.2	62.8	61.0	68.3	66.8	63.1

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

The significances for the other eight indicators are also inferred through respective sets of fuzzy rules. Table 8 shows the outcomes of fuzzy reasoning; however, the implication of an significance value is indecipherable if without comparing it with standard. Therefore, the SAT process intermingles significance with standards into acceptability in the following section.

3.2.2. SAT of significance into acceptability

The first part of SAT is to incorporate the standards into SAT through Eq. (1). In the casPe of the neutral risk attitude ($ri = 1$), the acceptabilities for all indicators in the respective THSR sections are obtained in Table 9. In the northern section, water (I_2) did not reach minimum acceptance (60), and noise (I_4), terrestrial (I_6) and aquatic (I_7) are not very acceptable, even when the mitigation measures were performed. In central and southern sections had results similar to those of the northern section. Moreover, the consequences of the entire line sums weighted the 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.

The section part of SAT is to incorporate the decision makers' risk attitude into SAT, as formulated in Eq. (2). In order to examine the distributions of the results varying on the decision makers' risk attitude, the acceptabilities for 'very optimistic risk attitude' ($ri = 0.63$), 'neutral risk attitude' ($ri = 1.0$) and 'very pessimistic risk attitude' ($ri = 1.6$) are viewed as the maximum, the median and the minimum values of the band values, as shown in Fig. 10. The range of a band value signifies the uncertainty of the results arising from the incomplete confidence of decision makers on the estimates of significances. Apparently, the adoption of the decision makers' risk attitude will greatly affect the evaluation results. For example, for PIWM in the northern section, nine out of ten indicators acquire higher acceptabilities than the minimum acceptance when an optimistic risk attitude is taken; whereas, with pessimistic risk attitude, only three indicators surpass the minimum acceptance (see Fig. 10a). In central and southern sections, the pessimistic risk attitude makes the evaluation results worse, two indicators remain acceptable (see Fig. 10b, c). Fig. 10d demonstrates the results of the entire line which sums weighted the conclusions for the three sections in terms of the rail-length proportion.

3.2.3. Overall evaluation via FANP

The overall acceptability of a proposal can be calculated by a weighted summation (Eq. (5)), where the global weights from w_1 to w_{10} derived by FANP (Section 2.4) 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. Finally, the overall acceptability of a proposal for 'very optimistic risk attitude' ($ri = 0.63$), 'neutral risk attitude' ($ri = 1.0$) and 'very pessimistic risk attitude' ($ri = 1.6$) (the maximum, the median and the minimum values of the band values, respectively) are delineated in Fig. 11. The results suggest that the proposal is acceptable with risk attitudes towards from very optimistic to pessimistic; however, it should be rejected if very pessimistic risk attitude is taken.

3.2.4. Cluster analysis

Cluster analysis identifies and classifies objects or variables on the basis of the similarity of their characteristics. Moreover, this analysis seeks to minimize within-cluster variance and maximize between-cluster variance. The results of cluster analysis constitute a number of heterogeneous clusters with homogeneous contents. Substantial differences exist between these clusters, but the objects within a single cluster are similar. Thus, if the classification is successful, the objects within-clusters will be proximate when plotted geometrically; whereas, different clusters will be peripheral.

In this study, the decline in the acceptability of the PIWM when compared to the BC was of particular concern because this decline reveals the level of environmental impact due to the construction

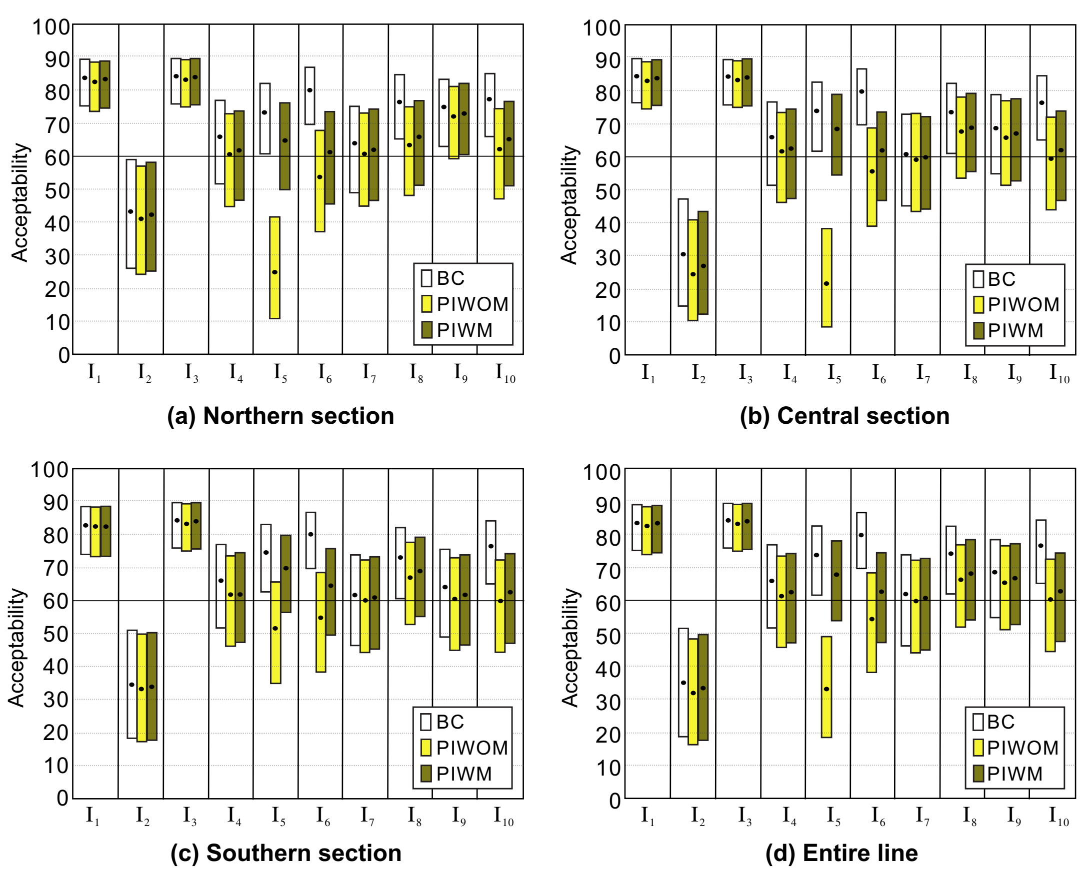

Fig. 10. The distributions of the acceptabilities for 10 indicators: from very optimistic to very pessimistic risk attitudes.

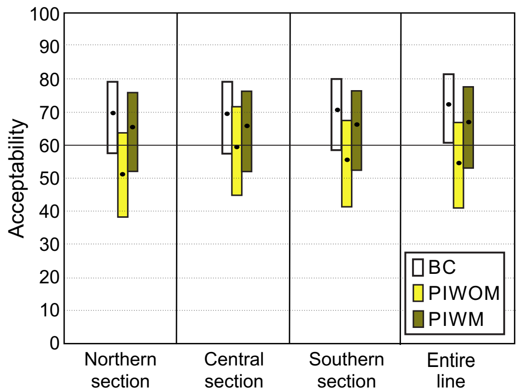

Fig. 11. The distributions of the overall acceptabilities for THSR project: from very optimistic to very pessimistic risk attitudes.

work. To interpret the impact, a non-hierarchical clustering technique, similar to importance–performance analysis (Martilla & James, 1977), was implemented on the basis of the influences of indicators (i.e., global weights) and the decline in levels of PIWM acceptabilities relative to the BC. The clustering began with the manual selection of a seed point (i.e., a hollow circles in Fig. 12) for each potential cluster, usually located at the centroid of all objects within the cluster. Each object must belong exclusively to a cluster whose seed point is nearest to this object.

Fig. 12 geometrically illustrates the three clusters in a coordinate graph where the *x*-axis represents the influence of the indicator (i.e., global weight) and the *y*-axis indicates the decline in acceptability due to the THSR project. Cluster A_i indicates the indicator with less influence but severe decline in acceptability. Terrestrial species, with low influences on other indicators, will receive a greater impact because of the destruction of their habitats. Besides, culture will also be subjected to a higher impact. The THSR project

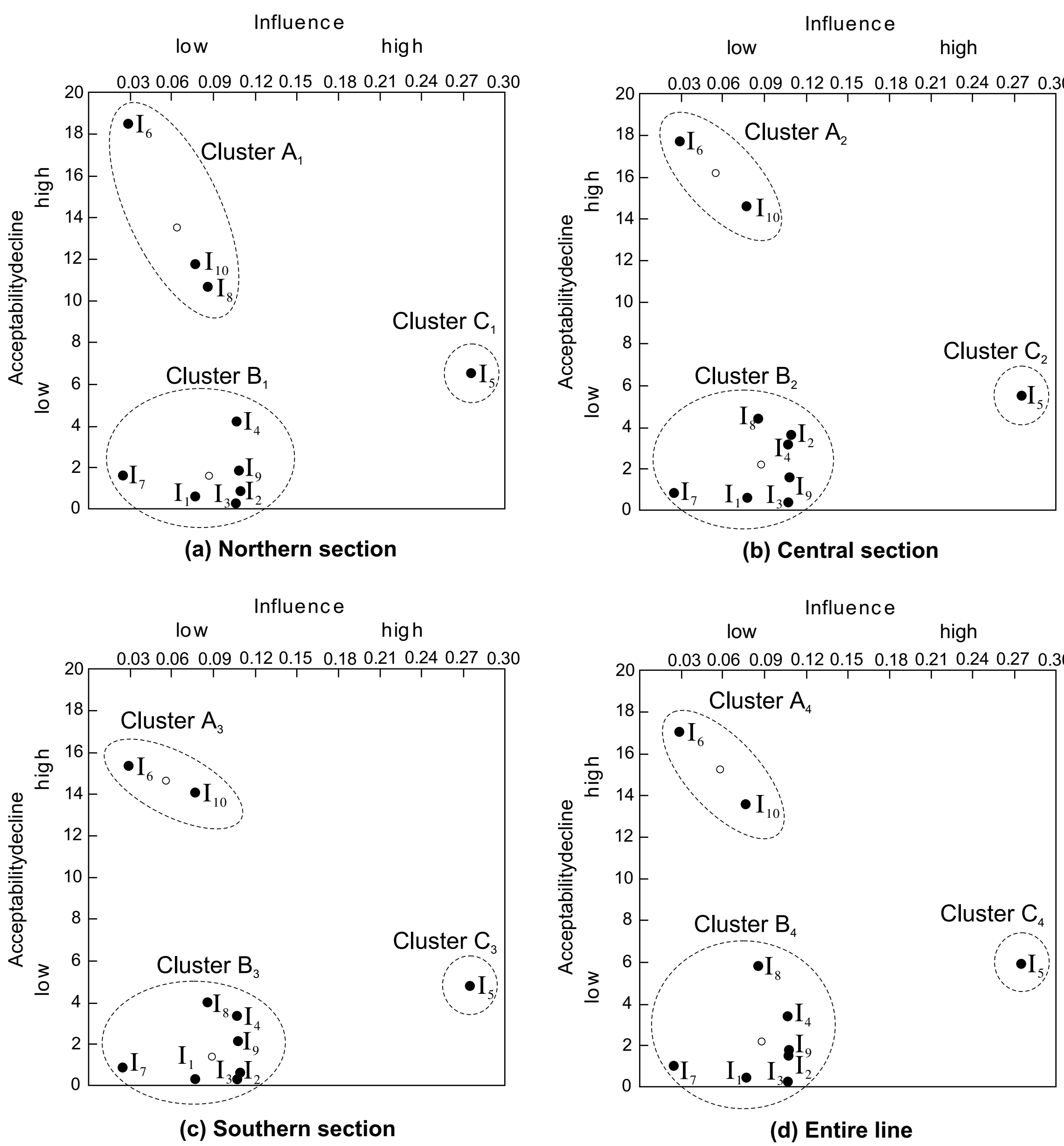

Fig. 12. Cluster analysis of evaluation results for PIWM.

should devise a superior plan to preserve the terrestrial species, cultural heritage and landscape. The rest of indicators converge into cluster B_i, representing low decline in acceptability and low influence. Even some indicators such as air, water, soil, aquatic and society will have a slight decline in acceptability. Cluster C_i denotes the indicator with low decline in acceptability and high influence. Despite this lower decline, construction waste heavily influences other indicators, thereby rendering it noteworthy.

4. Conclusion

A decision-support 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 framework is composed of the fuzzy logic, significance-acceptability transformation and fuzzy analytic network process, 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 facts and the fulfillment of social values and beliefs;
- equipped with the concept of risk via the inclusion of decision makers' risk attitude (tolerance).

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 the involvement of additional specialists to refine fuzzy rules and the use of statistics instead of experts' judgments to define the dependence among environmental factors.

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Appendix A. Fuzzy logic

An example of fuzzy reasoning, in which a new fuzzy value is derived on the basis of a fuzzy rule (i.e., the ith rule in a fuzzy rule-base) with three antecedents and three fuzzy facts, is represented as follows:

$$\frac{\text{IF } X_1 \text{ is } \widetilde{F}_{i1} \text{ AND } X_2 \text{ is } \widetilde{F}_{i2} \text{ AND } X_3 \text{ is } \widetilde{F}_{i3} \text{ THEN } Y \text{ is } \widetilde{G}_i X_1 \text{ is } \widetilde{F}'_1 \text{ AND } X_2 \text{ is } \widetilde{F}'_2 \text{ AND } X_3 \text{ is } \widetilde{F}'_3}{Y \text{ is } \widetilde{G}'_i}, \tag{A1}$$

where X_j and Y are linguistic variables; $\widetilde{F}_{ij}$ and $\widetilde{F}'_j$ are fuzzy sets of U_j; $\widetilde{G}_i$ and $\widetilde{G}'_i$ are fuzzy sets of V. In the framework of the compositional rule of inference (Zadeh, 1975), $\widetilde{G}'_i$ is computed by

$$\widetilde{G}'_i = (\widetilde{F}'_1 \wedge \widetilde{F}'_2 \wedge \widetilde{F}'_3) \circ ((\widetilde{F}_{i1} \wedge \widetilde{F}_{i2} \wedge \widetilde{F}_{i3}) \rightarrow \widetilde{G}_i), \tag{A2}$$

where $\wedge$ denotes a t-norm operator, $\circ$ is a composition operator and $\rightarrow$ indicates an implication operator.

Selection of operators is an important issue for calculating $\widetilde{G}'_i$. If 'sup-min' is chosen as the composition operator (Zadeh, 1973), the membership function of $\widetilde{G}'_i$ is computed by

$$\mu_{\widetilde{G}'_i}(v) = \max_{u_1,u_2,u_3} \min[\mu_{\widetilde{F}'_1 \wedge \widetilde{F}'_2 \wedge \widetilde{F}'_3}(u_1,u_2,u_3), \mu_{\widetilde{F}_{i1} \wedge \widetilde{F}_{i2} \wedge \widetilde{F}_{i3} \rightarrow \widetilde{G}_i}(u_1,u_2,u_3,v)]. \tag{A3}$$

Furthermore, if 'min' is treated as the t-norm operator (i.e., $a \wedge b = min(a,b)$) and Mamdani's implication operators are used (i.e., $a \rightarrow b = min(a,b)$), Eq. (A3) becomes the well-known 'Mamdani's fuzzy reasoning' (Mamdani, 1977), which can be expressed as

$$\mu_{\widetilde{G}'_i}(v) = \max_{u_1,u_2,u_3} \min[\mu_{\widetilde{F}'_1}(u_1), \mu_{\widetilde{F}'_2}(u_2), \mu_{\widetilde{F}'_3}(u_3), \mu_{\widetilde{F}_{i1}}(u_1), \mu_{\widetilde{F}_{i2}}(u_2), \mu_{\widetilde{F}_{i3}}(u_3), \mu_{\widetilde{G}_i}(v)]. \tag{A4}$$

Eq. (A4) can be further depicted in another form

$$\mu_{\widetilde{G}'_i}(v) = \min[\max_{u_1} \mu_{\widetilde{F}'_1 \wedge \widetilde{F}_{i1}}(u_1), \max_{u_2} \mu_{\widetilde{F}'_2 \wedge \widetilde{F}_{i2}}(u_2), \max_{u_3} \mu_{\widetilde{F}'_3 \wedge \widetilde{F}_{i3}}(u_3), \mu_{\widetilde{G}_i}(v)], \tag{A5}$$

where $(\widetilde{F}'_j \wedge \widetilde{F}_{ij})$ denotes the intersection of fuzzy sets $\widetilde{F}'_j$ and $\widetilde{F}_{ij}$; $\max_{u_j} \mu_{\widetilde{F}'_j \wedge \widetilde{F}_{ij}}(u_j)$ is the highest degree of membership of the intersection and can be interpreted as the compatibility C_{ij} between $\widetilde{F}'_j$ and $\widetilde{F}_{ij}$; $\min\{\max_{u_1} \mu_{\widetilde{F}'_1 \wedge \widetilde{F}_{i1}}(u_1), \max_{u_2} \mu_{\widetilde{F}'_2 \wedge \widetilde{F}_{i1}}(u_2), \max_{u_3} \mu_{\widetilde{F}'_3 \wedge \widetilde{F}_{i1}}(u_3)\}$ can be viewed as the overall compatibility C_i between the facts and the rule; and C_i is used to truncate $\widetilde{G}_i$ to obtain $\widetilde{G}'_i$. Moreover, if $\widetilde{F}'_j$ is a precise value (i.e., say $\overline{u}_j$), Eq. (A5) becomes

$$\mu_{\widetilde{G}'_i}(v) = \min\{\mu_{\widetilde{F}_{i1}}(\overline{u}_1), \mu_{\widetilde{F}_{i2}}(\overline{u}_2), \mu_{\widetilde{F}_{i3}}(\overline{u}_3), \mu_{\widetilde{G}_i}(v)\} \tag{A6}$$

where $(\min\{\mu_{\widetilde{F}_{i1}}(\overline{u}_1), \mu_{\widetilde{F}_{i2}}(\overline{u}_2), \mu_{\widetilde{F}_{i3}}(\overline{u}_3)\})$ can be viewed as the overall compatibility C_i between the facts and the rule; C_i is used to truncate $\widetilde{G}_i$ to obtain $\widetilde{G}'_i$.

If 'product' substitutes for 'min' as the t-norm operator (i.e., $a \wedge b = a \cdot b$), Eq. (A5) is modified as

$$\mu_{\widetilde{G}'_i}(v) = \max_{u_1,u_2,u_3} \min[\mu_{\widetilde{F}'_1}(u_1) \cdot \mu_{\widetilde{F}'_2}(u_2) \cdot \mu_{\widetilde{F}'_3}(u_3), \mu_{\widetilde{F}_{i1}}(u_1) \cdot \mu_{\widetilde{F}_{i2}}(u_2) \cdot \mu_{\widetilde{F}_{i3}}(u_3), \mu_{\widetilde{G}_i}(v)]. \tag{A7}$$

Likewise, if $\widetilde{F}'_j$ is a precise value (i.e., $\overline{u}_j$), Eq. (A7) evolves into

$$\mu_{\widetilde{G}'_i}(v) = \min\{\mu_{\widetilde{F}_{i1}}(\overline{u}_1) \cdot \mu_{\widetilde{F}_{i2}}(\overline{u}_2) \cdot \mu_{\widetilde{F}_{i3}}(\overline{u}_3), \mu_{\widetilde{G}_i}(v)\} \tag{A8}$$

where $(\mu_{\widetilde{F}_{i1}}(\overline{u}_1) \cdot \mu_{\widetilde{F}_{i2}}(\overline{u}_2) \cdot \mu_{\widetilde{F}_{i3}}(\overline{u}_3))$ can be viewed as the overall compatibility C_i between the facts and the rule; C_i is used to truncate $\widetilde{G}_i$ to obtain $\widetilde{G}'_i$.

In this paper, 'product,' 'sup-min,' and 'min' are selected as the t-norm, composition and implication operators, respectively. It should be noted that 'product' is chosen as the t-norm operator instead of another more widely used t-norm operator, 'min,' because the t-norm operator 'product' makes the result of $\widetilde{G}'_i$ sensitive to every input; whereas, only one input will control $\widetilde{G}'_i$ in the case of the t-norm operator 'min'.

Appendix B. Fuzzy preference programming method (Mikhailov & Madan, 2003)

Consider a pairwise comparison matrix $\widetilde{A}^{\alpha}_j$ consisting of interval judgment $a_{ik} = (l_{ik}, u_{ik})$, where l_{ik} and u_{ik} are the lower and the upper bounds of the corresponding interval judgment. When those judgments are consistent, there are many priority vectors $w = (w_{1j}(\alpha), \ldots, w_{nj}(\alpha))$, whose elements satisfy the inequalities

$$l_{ik} \leqslant \frac{w_{ij}(\alpha)}{w_{kj}(\alpha)} \leqslant u_{ik}, \tag{B1}$$

where $i = 1 \sim n-1$ and $k = 2 \sim n$ because the upper triangular part of $\widetilde{A}_j^\alpha$ is considered.

In the inconsistent cases, however, there is no such priority w vector satisfying all interval judgments simultaneously. But it is reasonable to try to find a vector that satisfies all judgments 'as well as possible'. This means that a good enough solution has to satisfy all judgments approximately, keeping the violations close to zero, or

$$l_{ik} \tilde{\leqslant} \frac{w_{ij}(\alpha)}{w_{kj}(\alpha)} \tilde{\leqslant} u_{ik}, \tag{B2}$$

where the symbol $\tilde{\leqslant}$ denotes the statement 'fuzzy less or equal to.'

In order to represent the prioritization problem as a linear function of all decision variables, the double-side inequalities (B2) is transformed into a set of single-side linear fuzzy inequalities

$$\begin{aligned} &w_{ij}(\alpha) - u_{ik} w_{kj}(\alpha) \tilde{\leqslant} 0, \\ &-w_{ij}(\alpha) + l_{ik} w_{kj}(\alpha) \tilde{\leqslant} 0. \end{aligned} \tag{B3}$$

The above set of $n(n-1)$ fuzzy constraints is given in a matrix form as

$$Rw \tilde{\leqslant} 0, \tag{B4}$$

where the matrix $R \in \Re^{m \times n},\ m = n(n-1)$.

The rth row of (B4), denoted by $Rw \tilde{\leqslant} 0$ represents a fuzzy linear constraint and might be defined by a linear membership function of the type

$$m_r(R_r w) = \begin{cases} 1 - \frac{R_r w}{d_r}, & R_r w \leqslant d_r, \\ 0, & R_r w \geqslant d_r, \end{cases} \tag{B5}$$

where d_r is a tolerance parameter, defined by the decision maker, which corresponds to the admissible interval of approximate satisfaction of the crisp inequality $R_r w \leqslant d_r,\ r = 1, 2, \ldots, m$.

The membership function (B5) represents the decision-makers' satisfaction with the fulfillment of the single-side constraints (B3). The value of $m_r(R_r w)$ is equal to zero when the corresponding crisp constraint $R_r w \leqslant d_r$ is strongly violated. The degree of membership takes values between zero and one when the crisp constraint is approximately satisfied and it is greater than one if the constraint is fully satisfied.

The solution to the prioritization problem by the FPP method is based on two additional assumptions. The first one requires the existence of non-empty fuzzy feasible area $\widetilde{P}$ on the simplex hyperplane Q^{n-1}

$$Q^{n-1} = \left\{ (w_{1j}(\alpha), \ldots, w_{nj}(\alpha) | w_{ij}(\alpha) > 0, \sum_{i=1}^{n} w_{ij}(\alpha) = 1 \right\}. \tag{B6}$$

The membership function of the fuzzy feasible area is expressed as the intersection of all interval membership functions (B5), i.e.

$$m_{\widetilde{P}(w)} = [min\{m_1(R_1 w), \ldots, m_m(R_m w) | w \in Q^{n-1}] \tag{B7}$$

The second assumption of the FPP method specifies a selection rule, which determines a priority vector having the highest degree of membership in the aggregated membership function (B7). It can easily be proved that $\widetilde{P}$ is a convex set, so there is always a priority vector w in Q^{n-1} that has a maximum degree of membership λ

$$\lambda = m_{\widetilde{P}}(w^*) = \max[min\{m_1(R_1 w), \ldots, m_m(R_m w) | w \in Q^{n-1}]. \tag{B8}$$

The maximin prioritization problem (B8) can be represented as the following fuzzy programming problem:

$$\begin{aligned} \text{maximize} \quad & \lambda, \\ \text{subject to} \quad & d_r \lambda + R_r w \leqslant d_r, \\ & \sum_{i=1}^{n} w_{ij}(\alpha) = 1, \\ & w_{ij}(\alpha) > 0, \quad i = 1, 2, \ldots, n, \\ & r = 1, 2, \ldots, m, \quad m = n(n-1). \end{aligned} \tag{B9}$$

The optimal solution to the above problem is a vector (w^*, λ_α^*), whose first component represents the priority vector that maximizes the degree of membership in the fuzzy feasible area, whereas, the second one gives the value of the maximum degree, $\lambda_\alpha^* = m_{\widetilde{P}}(w^*)$. The value of λ_α^* measures the degree of satisfaction and is a natural indicator for the inconsistency of the decision-makers judgments, so it is called a consistency index. When the human interval judgments are consistent, λ_α^* is greater than or equal to one. For inconsistent judgments, the consistency index takes a value between one and zero, depending on the degree of inconsistency and the values of the tolerance parameters d_r. It can be shown that the corresponding maximizing solution w^* represents a point in the feasible area for which some of the ratios $(R_r w / d_r)$ are equal to λ_α^*.

References

Borri, D., Concilio, G., & Conte, E. (1998). A fuzzy approach for modeling knowledge in environmental systems evaluation. *Computers, Environment and Urban Systems, 22*(3), 299–313.

Brent, A. C., Rogers, D. E. C., Ramabitsa-Siimane, T. S. M., & Rohwer, M. B. (2007). Application of the analytical hierarchy process to establish health care waste management systems that minimise infection risks in developing countries. *European Journal of Operational Research, 181*, 403–424.

Canter, L. (1996). *Environmental Impact Assessment*. Singapore: McGraw-Hill.

Canter, L. W., & Canty, G. A. (1993). Impact significance determination basic considerations and a sequenced approach. *Environmental Impact Assessment Review, 13*, 275–297.

Cheng, E. W. L., & Li, H. (2005). Analytic network process applied to project selection. *Journal of Construction Engineering and management (ASCE), 131*, 459–466.

Cloquell-Ballester, V. A., Monterde-Diaz, R., Cloquell-Ballester, V. A., & Santamarina-Siurana, M. C. (2007). Systematic comparative and sensitivity analyses of additive and outranking techniques for supporting impact significance assessments. *Environmental Impact Assessment Review, 27*, 62–83.

Duinker, P. N., & Beanlands, G. E. (1986). The significance of environmental impacts: An exploration of the concept. *Environmental Management, 10*(1), 1–11.

Dzidzornu, D. M. (2001). Environmental impact assessment procedure through the conventions. *European Environmental Law Review, 10*(1), 15–27.

González, B., Adenso-Díaz, B., & González-Torre, P. L. (2002). A fuzzy logic approach for the impact assessment in LCA. *Resources, Conservation and Recycling, 37*, 61–79.

Kontic, B. (2000). Why are some experts more credible than others? *Environmental Impact Assessment Review, 20*(4), 427–434.

Liu, K. F. R. (2007). Evaluating environmental sustainability: An integration of multiple-criteria decision-making and fuzzy logic. *Environmental Management, 39*, 721–736.

Mamdani, E. H. (1977). Applications of fuzzy logic to approximate reasoning using linguistic synthesis. *IEEE Transactions on Computers, 26*(12), 1182–1191.

Martilla, J. A., & James, J. C. (1977). Importance–performance analysis. *Journal of Marketing, 41*(1), 77–79.

Marusich, L. J., & Wilkinson, P. F. (2001). The application of fuzzy logic analysis to assessing the significance of environmental impacts: Case studies from Mexico and Canada. Report for the Canadian Environmental Assessment Agency. <http://www.ceaa-acee.gc.ca/015/001/012/index_e.htm>.

Mikhailov, L., & Madan, G. (2003). Fuzzy analytic network process and its application to the development of decision support system. *IEEE Transactions on Systems, Man, and Cybernetics-Part C: Application and Reviews, 33*(1), 33–41.

Ong, S. K., Koh, T. H., & Nee, A. Y. C. (2001). Assessing the environmental impact of material processing techniques using an analytical hierarchy process method. *Journal of Materials Processing Technology, 113*, 424–431.

Ramanathan, R. (2001). A note on the use of the analytic hierarchy process for environmental impact assessment. *Journal of Environmental Management, 63*, 27–35.

Roussel, O., Cavelier, A., & Van der Werf, H. M. G. (2000). Adaptation and use of a fuzzy expert system to assess the environmental effect of pesticides applied to field crops. *Agriculture, Ecosystems and Environment, 80*, 143–158.

Saaty, T. L. (1990). *The Analytic Hierarchy Process*. New York: Pergamon Press.

Saaty, T. L. (2001). *Decision making with dependence and feedback: The analytic network process. Pittsburgh, PA: RWS.*

Shepard, R. B. (2005). *Quantifying environmental impact assessments using fuzzy logic*. New York: Springer.

Siqueira Campos Boclin & Mello, R. (2006). A decision support method for environmental impact assessment using a fuzzy logic approach. *Ecological Economics, 58, 170–181.*

Sólnes, J. (2003). Environmental quality indexing of large industrial development alternatives using AHP. *Environmental Impact Assessment Review, 23*, 283–303.

Srdjevic, B. (2007). Linking analytic hierarchy process and social choice methods to support group decision-making in water management. *Decision Support Systems, 42*, 2261–2273.

Tesfamariam, S., & Sadiq, A. R. (2006). Risk-based environmental decision-making using fuzzy analytic hierarchy process (F-AHP). *Stochastic Environmental Research and Risk Assessment, 21*, 35–50.

Tran, L. T., Gregory, K. C., O'Neill, R. V., & Smith, E. R. (2004). Integrated environmental assessment of the mid-Atlantic region with analytical network process. *Environmental Monitoring and Assessment, 94*, 263–277.

Tsamboulas, D., & Mikroudis, G. (2000). EFECT: Evaluation framework of environmental impacts and costs of transport initiatives. *Transportation Research Part D: Transport and Environment, 5*, 283–303.

Van der Werf, H. M. G., & Zimmer, C. (1998). An indicator of pesticide environmental impact based on a fuzzy expert system. *Chemosphere, 36*(10), 2225–2249.

Zadeh, L. A. (1973). Outline of a new approach to the analysis of complex systems and decision processes. *IEEE Transactions on Systems, Man and Cybernetics, 3*, 28–44.

Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning. *Information Sciences, 8*(3), 199–249.

Zadeh, L. A. (1996). Fuzzy logic = computing with words. *IEEE Transactions on Fuzzy Systems, 4*(2), 103–111.