Hierarchical Analytic Fuzzy Evaluation System (HAFES)

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1. Introduction

Environmental assessment is a multidimensional decision support tool incorporating various decision criteria. According to the research literature, the analytic hierarchy process (AHP) (Saaty, 1980), a multi-criteria decision analysis method, is implemented in different types of environmental assessment and management schemes. Banerjee et al. (2018a), Banerjee et al. (2018b), Bottero et al. (2011), Garfi et al. (2011), Hermann et al. (2007), Ramanathan (2001), Reza et al. (2011), and Ruiz-Padillo et al. (2016) conducted some of the previous case studies.

The AHP is employed to draw pairwise comparisons between criteria in order to give them importance weights, which ultimately lead to the ranking of decision alternatives.

Moreover, the AHP can be combined with other tools for performance evaluation. As a case in point, Hermann *et al.* (2007) assessed the environmental performance of a pulp production system by integrating the AHP with lifecycle assessment (LCA) and environmental performance indicators. The AHP was utilized to determine the importance weights of the LCA impact categories from global, regional, and local perspectives.

The Battelle environmental evaluation system (Dee *et al.*, 1973) is a method for conducting environmental impact analysis. The environmental evaluation system (EES) structures the problem into a hierarchy including four major categories partitioned into eighteen components and seventy-eight parameters, i.e. the measured criteria at the lowest tier.

The parameters are converted into a common unit within the range [0, 1] through "value functions". The values of zero and one indicate "very poor" and "very good" quality, respectively.

The "parameter importance units" represent importance weights, determined through the value judgements of the design team at Battelle Columbus Laboratories. These importance units add up to a total score of 1000.

Finally, the scaled parameters are multiplied by their importance weights and summed up to yield the final scores, utilized to draw comparisons between alternatives (http://ponce.sdsu.edu/the_battelle_ees.html, 2019).

It is important to note that alternatives themselves may also produce criterial importance (Saaty and Vargas, 2013). In other words, underlying conditions may influence the importance degrees of criteria. The analytic network process (ANP) (Saaty, 1996) considers such influences in comparing decision alternatives.

This fact could be of vital importance to environmental assessment, in which applying fixed criteria importance weights to all scenarios might lead to undesirable or unsustainable conclusions.

Moreover, fuzzy expert systems such as Mamdani and Sugeno fuzzy inference systems are useful tools for environmental assessment as they help evaluate the environmental performance of a system through fuzzy reasoning taking account of criteria's values as well as their contextual importance. Actually, criteria's importance weights are implicit in the linguistic terms, representing fuzzy sets used in the defined if-then rules.

Such systems are expeditious tools, especially when it comes to scrutinize numerous design alternatives within a real-time framework.

Regarding environmental assessment, for example, Liu *et al.* (2009), Siqueira Campus Boclin, and Mello (2006) employed hierarchical Mamdani-type fuzzy expert systems, whereas Givargis *et al.* (2018) compared the applications of binary hierarchical Mamdani and zero order Sugeno-type fuzzy expert systems.

This article aims to propose the basics of an expert system for environmental assessment, called the hierarchical analytic fuzzy evaluation system (HAFES), designed on the AHP, EES, and the linear Sugeno type fuzzy system.

The main feature of the HAFES is the explicit incorporation of the criteria's importance preferences into the consequent parts of the if-then rules.

2. HAFES

Sub-Section 2.1 provides instructions on how to develop the HAFES, and subsection 2.2 presents a brief illustrative practical example of the system.

2.1. Developing the HAFES

The HAFES is developed through the following steps.

2.1.1. Structuring the Hierarchy

In this step, the problem is structured into a hierarchy. The hierarchical structure helps reduce the number of rules (Aly and Vrana, 2007) and pairwise comparisons. Furthermore, the binary structure (Fig.1) obviates the need for the consistency check of AHP's pairwise comparisons. For illustrative purposes, Fig.1 exhibits a brief and general architecture of an HAFES.

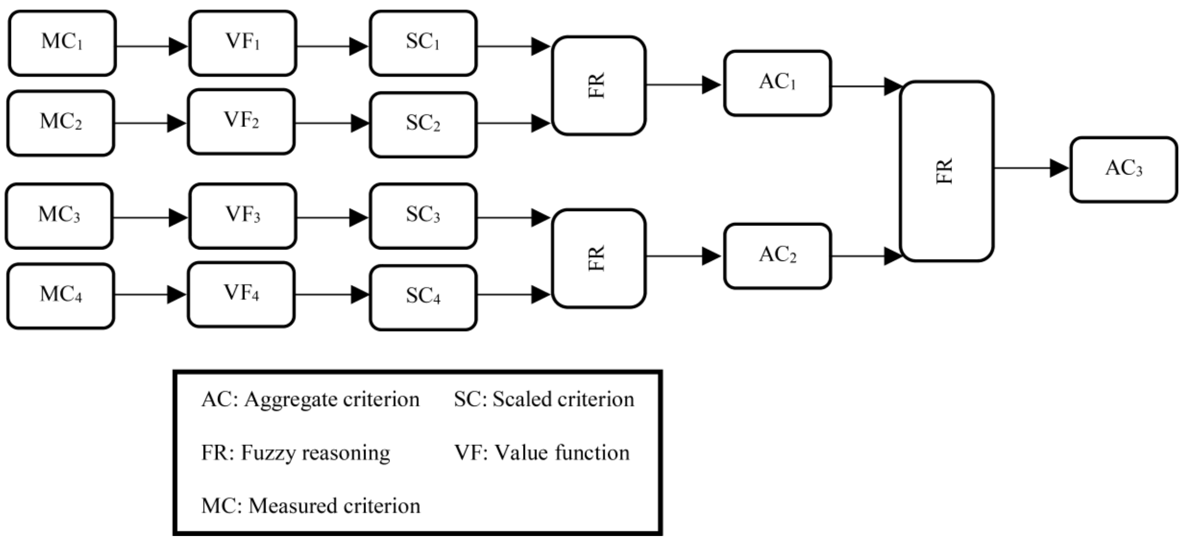

Fig.1. A brief and general architecture of an HAFES

According to Fig.1, the measured criteria are the measurable or predictable parameters in both objective and subjective manners. For instance, NOx and visual intrusion are objective and subjective criteria, respectively.

The scaled criteria are those parameters converted into a common range through value functions. These criteria are integrated into the aggregate criteria through fuzzy reasoning. Similarly, the aggregate criteria themselves make stepwise combinations by means of fuzzy reasoning towards the end of the hierarchy to determine the final score.

The human-ecosystem health and socioeconomic criteria are good exemplars of the aggregate criteria in environmental assessment that are integrated into the sustainability criterion, representing the environmental or sustainability performance of a system.

2.1.2. Scaling

The criteria at the lowest tier of the hierarchy, i.e. the measured criteria, are converted into a common range [0, 1] through value functions that could be of any type, e.g. triangular, semi-trapezoid, sigmoid, etc. The zero value represents extremely poor quality, whereas the value of one represents extremely good quality. The scaled values are then passed onto fuzzy reasoning for further processing.

2.1.3. Fuzzy Reasoning

2.1.3.1. Fuzzification

A common fuzzy scale is defined to represent the quality of criteria's values. The scale contains fuzzy membership functions, representing fuzzy sets, through which the input values within the range [0, 1] are mapped onto membership degrees within the range [0, 1]. The membership degree reflects the grade to which an input value belongs to a fuzzy set. The fuzzy sets and their corresponding membership functions are expressed in linguistic terms (Fig.2 in Section 2.2).

2.1.3.2. Weighting

Weighting is an integral part of the HAFES (Fig. 3 in Section 2.2). Criteria's weights are the outcomes of the rule base containing logical rules.

Every logical rule in the rule base uses an "if-then" statement to connect the linguistic terms corresponding to criteria's values in order to draw inferences in the consequent section.

The consequent part of a rule is where weighting is actually administered to criteria. The weighting process is performed by means of the AHP method, through which the criteria are compared in a pairwise manner by using a preference scale ranging from 1 to 9 represented by linguistic terms from "equally preferred" to "extremely preferred".

2.1.3.3. Aggregation

In this step, the weighted sum method (Eq. 1) is applied to every single rule in the rule base to determine the output value of that rule.

$$y_i = \sum_{j=1}^{N} \left(w_{ij} \times x_j\right) \tag{1}$$

Where,

y_i: The output of the *i*th rule.

w_{ij}: The weight of the *j*th input criterion related to the *i*th rule

x_j: The value of the *j*th input criterion.

2.1.3.4. Defuzzification

In this step, the results of all rules are averaged to determine the final output as follows:

$$Y = \sum_{i=1}^{M} \left(y_i \times \mu_i\right) \Big/ \sum_{i=1}^{M} \mu_i \tag{2}$$

Where,

Y : The final output.

y_i : The output of the *i*th rule.

μ_i : The firing strength of the *i*th rule that is returned as follows:

$$\mu_i = Min\left(\mu(x_j)\right) \tag{3}$$

Where,

$\mu(x_j)$: The membership degree of the *j*th input criterion's value in the corresponding fuzzy set per rule

2.2. Brief Illustrative Example

In this brief hypothetical example, the human-ecosystem health and socioeconomic criteria, the scores of which are the resultant of their antecedent criteria's scores throughout the hierarchy, are taken into consideration. The scores of these criteria are combined to deliver the sustainability score representing the result of the hierarchy. These components are the pillars of sustainability; therefore, underestimating either of them to the benefit of the other may compromise sustainability.

The human-ecosystem health criterion is the composite of the human health and ecosystem health criteria, whereas the socioeconomic criterion is the combination of the social and economic criteria. All of the mentioned criteria can be traced back to the measured criteria, i.e. the parameters.

Table 1 presents the human-ecosystem health and socioeconomic criteria scores resulted from the performance of an imaginary project.

Table 1. The scores of the scrutinized criteria

Criteria	Score
Human-ecosystem health	0.4
Socio-economic	0.8

According to Table 1, it can logically be argued, from a broader perspective, that low human-ecosystem health quality value may affect the socioeconomic component. However, to better demonstrate how the situation-based weighting can prevent biased conclusions, the problem is scrutinized from a narrower perspective in this example.

Figs. 2 and 3 display the common fuzzy scale and the rule base, respectively.

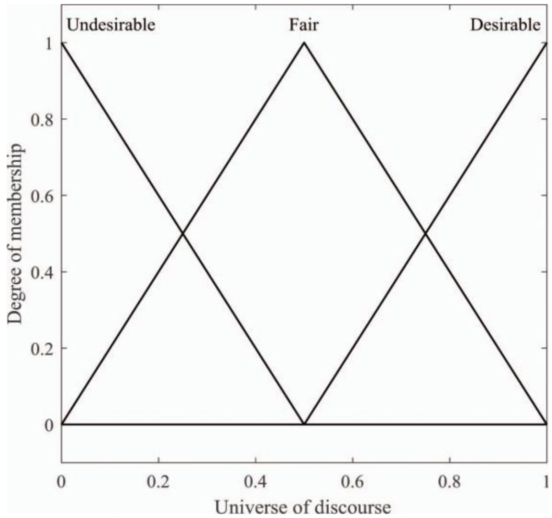

Fig.2. The common fuzzy scale

1) If human-ecosystem health is undesirable and socio-economic is undesirable, then human-ecosystem health is equally preferred to socio-economic.
2) If human-ecosystem health is undesirable and socio-economic is fair, then human-ecosystem health is strongly preferred to socio-economic.
3) If human-ecosystem health is undesirable and socio-economic is desirable, then human-ecosystem health is extremely preferred to socio-economic.
4) If human-ecosystem health is fair and socio-economic is undesirable, then socio-economic is strongly preferred to human-ecosystem health.
5) If human-ecosystem health is fair and socio-economic is fair, then human-ecosystem health is equally preferred to socio-economic.
6) If human-ecosystem health is fair and socio-economic is desirable, then human-ecosystem health is equally to moderately preferred to socio-economic.
7) If human-ecosystem health is desirable and socio-economic is undesirable, then socio-economic is extremely preferred to human-ecosystem health.
8) If human-ecosystem health is desirable and socio-economic is fair, then socio-economic is equally to moderately preferred to human-ecosystem health.
9) If human-ecosystem health is desirable and socio-economic is desirable, then human-ecosystem health is equally preferred to socio-economic.

The AHP comparison scale:
1: Equally preferred
2: Equally to moderately preferred
3: Moderately preferred
4: Moderately to strongly preferred
5: Strongly preferred
6: Strongly to very strongly preferred
7: Very strongly preferred
8: Very strongly to extremely preferred
9: Extremely preferred

Fig. 3. The rule base

Table 2. The results of fuzzification

Criteria	Undesirable	Fair	Desirable
Human-ecosystem health	0.2	0.8	0
Socioeconomic	0	0.4	0.6

Table 3. The results of weighting and aggregation

Rules	μ_i^a	W_H^b	W_S^c	Aggregate scores
1	0	0.5	0.5	0.000
2	0.2	0.83	0.17	0.094
3	0.2	0.9	0.1	0.088
4	0	0.17	0.83	0.000
5	0.4	0.5	0.5	0.240
6	0.6	0.67	0.33	0.319
7	0	0.1	0.9	0.000
8	0	0.33	0.67	0.000
9	0	0.5	0.5	0.000

a: The firing strength of the rule
b: The weight of the human-ecosystem criterion
c: The weight of the socioeconomic criterion

Table 4. The final score and its membership degrees

Sustainability score	Undesirable	Fair	Desirable
0.529	0.000	0.942	0.058

According to Table 3 and Fig.3, it is evident that the weights are evenly distributed between the human-ecosystem health and socioeconomic criteria in which their values belong to the same fuzzy set. This fact is pronounced in rules 1, 5, and 9.

Moreover, as it can be seen from the rest of the rules, the weighting is in favor of the criteria with lower quality to avoid compromising the concept of sustainability.

According to Table 4 along with Table 1 it can be observed that the lower quality value of the human-ecosystem health criterion has greater influence on the sustainability score than its socioeconomic counterpart.

To put it another way, with due regard to Tables 2 and 4, the undesirable-fair performance of the hypothetical project with respect to the human-ecosystem health criterion influences the sustainability score in such a way that it falls within the "fair" category nearly right in the middle of the common scale with a minimal membership degree to the "desirable" fuzzy set.

3. Outlook

The measured criteria (the parameters) are pivotal to the HAFES since they lay the foundations upon which the hierarchy is built. Hence, the methods through which these parameters are identified and computed determine the size of the hierarchy and the validity of evaluation.

Causal networks (Perdicoúlis and Glasson, 2006; Perdicoúlis and Glasson, 2009) and integrated environmental modeling (Laniak *et al.*, 2013) hold out promising prospects for environmental assessment. These methods could be utilized as much as possible to identify and determine the HAFES parameters.

Causal networks can help identify tangible midpoint and endpoint parameters resulting from some other parameters. For instance, for a highway project, both traffic noise and air pollution could synergistically affect human health and property values. Human health can be used as an endpoint parameter, whereas property value can be treated as a midpoint one subsumed by the economic criterion. In this manner, there will be no need to directly incorporate air and noise parameters, which will consequently result in scaling down the hierarchy and, therefore, facilitating the evaluation process.

Furthermore, causal networks are able to provide a roadmap for integrated modeling that has the capacity, through validated models, to determine the tangible parameters more realistically. For the highway project example, traffic noise and air pollution models can collectively feed into human risk and hedonic price models to determine the impacts on human health and property values, respectively.

4. Conclusions

The HAFES is a rule-based system that integrates fuzzy reasoning with the AHP and the EES principles in order to measure the environmental performance of current or expected systems. The weights of criteria are determined relative to their quality values in an explicit fashion through pairwise comparisons in the consequent part of the rules. The integration of the HAFES with causal networks and integrated environmental modeling will conceivably culminate in concise hierarchies and more realistic environmental evaluation.

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