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COMPARING MAMDANI AND SUGENO HIERARCHICAL FUZZY SYSTEMS FOR ENVIRONMENTAL IMPACT ASSESSMENT: A PIPELINE PROJECT CASE STUDY

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Abstract

Several studies have been conducted in various fields comparing Mamdani and Sugeno fuzzy inference systems (FISs). This study contributes to the literature by comparing the performance of Mamdani and Sugeno hierarchical fuzzy systems (HFSs) in terms of their technical performance within the context of environmental impact assessment (EIA), a multi-criteria decision analysis (MCDA) method, with the aim of illuminating practical issues that need to be taken into account during application. The context is a non-commercial, research-oriented EIA of a pipeline project in southern Iran. Mamdani and Sugeno HFSs were developed with data collected for and expertise gained via a previous formal EIA of the same project. The two developed HFSs were of binary structure, reducing complexity while also facilitating sensitivity analysis. A sensitivity analysis was carried out with the full range of possible HFS input values. Excluding the final FISs, the FIS outputs did not differ significantly between the two examined HFSs. However, the behavior of the Sugeno HFS was found to be more linear than that of its Mamdani counterpart with a higher degree of sensitivity to input value changes. This study indicates that the Mamdami HFS is unreliable in some areas due to fluctuations in the output surface, which necessitates smoothing before it can be applied.

Key words: environmental impact assessment, hierarchical fuzzy system, Mamdani inference system, Sugeno inference system

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1. Introduction

Environmental impact assessment (EIA) is a process of systematic identification and evaluation of the potential impacts of projects, programs, or legislative actions on the physical, chemical, biological, cultural, and socioeconomic constituents of the "total environment" (Canter, 1996). It is a multi-criteria decision analysis method enables various alternatives to be evaluated in relation to multifarious criteria, such that each alternative is considered in relation to criteria weighted on the basis of decision makers' or stakeholders' judgments. Ultimately, EIA yields total scores for each alternative that reflect decision makers' preferences alongside the alternatives' performance in relation to the criteria (FEI, 2013; Torretta and Capodaglio, 2017). According to Rodriguez-Bachiller and Glasson, (2004), EIA implementation has been improving, and a standardized practice is close to being defined. Nevertheless, most EIAs are far from satisfactory and new paradigms for EIA are being proposed in the literature. Rodriguez-Bachiller and Glasson (2004) propose that expert systems be integrated with geographical information systems (GISs), whereas Shepard (2005) advocates the use of approximate

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reasoning and fuzzy modeling. Subjective judgment is an inextricable component of EIA because it entails social and cultural value judgments as well as scientific data. Traditional multi-criteria decision-making methods are insufficient for informing decisions because they are not able to model qualitative human thinking processes. Conversely, fuzzy logic has the capacity to deal with such criteria and problems. Fuzzy systems compute numerical outputs based on a "qualitative human thinking process" that uses words to analyze complex systems (Chen et al., 2017; Liu et al., 2006). As a result, fuzzy expert systems can help stakeholders understand the rationale behind the tangible values computed by an EIA (Aly and Vrana, 2007; Pislaru et al., 2010). Likewise, these systems can provide a tool that stakeholders can use to incorporate their views and preferences into the assessment process and observe the numerical results of their reasoning. A fuzzy expert system is a knowledge-based, quantitative expert system that functions using fuzzy sets, membership functions, if-then rules, and logical operators such as "AND", "OR", and "NOT" (Horsekotte, 2005; Shepard, 2005). Mamdani and Sugeno models are the most commonly employed fuzzy expert systems (Zaheeruddin and Jane, 2006). The main feature of the Mamdani fuzzy inference system (FIS) is the fact that both the antecedents and consequents of its rules are fuzzy. Building this type of model requires four steps: fuzzification, implication, aggregation, and defuzzification (Mathworks Inc., 2006).

The Sugeno system (a.k.a. TSK based on its originators Takagi, Sugeno and Kang) is similar to the Mamdani system in the fuzzification step and its use of fuzzy operators. However, it is distinguished by the feature of having output membership functions that are not fuzzy. The Sugeno system can employ a linear (first-order) output membership function or a constant (zero-order) membership function (Mathworks Inc., 2006; Zaheeruddin and Jane, 2006), and its final output is computed through the weighted average method with the outputs of fired rules (Mathworks Inc., 2006).

In standard fuzzy systems, the number of rules and parameters increases exponentially in relation to the number of input variables. This so-called curse of dimensionality damages the transparency of systems since humans are unable to understand and justify "hundreds or thousands of fuzzy rules and parameters" (Wang et al., 2006). This problem has been addressed by hierarchical fuzzy systems (HFSs), which preclude a large number of expert rules, prevent the expansion of knowledge into a colossal system, and support the organization of inter-input variable relationships into a logical structure. Hierarchical systems accomplish this restraint by combining or aggregating several smaller fuzzy expert systems into the computation of the final result.

In this context, combination means that the outputs of logically-related fuzzy expert systems are integrated into a single output using logical rules, whereas aggregation means that the outputs of independent fuzzy expert systems are accumulated as necessary for computing the final output of the entire system (Aly and Vrana, 2007).

The purpose of the present work is to compare the technical performance of Mamdani and Sugeno HFSs in the realm of EIA from a multi-criteria decision analysis perspective with the aim of highlighting some crucial aspects of utilizing the developed models. These HFS models have probable applications in future studies of similar situations. The present study is not a real EIA and does not analyze and compare any actual alternatives, which would be beyond the capacity of this paper. Rather, it scrutinizes the way both systems can behave in supporting environmental decisions.

Two EIA case studies utilizing HFSs are summarized herein. These studies laid the foundation upon which the current study builds and to which this work adds new features and provides new practical insights. This study utilizes a simplified structure relative to the mentioned studies via developing binary HFSs. In section 2, a brief discussion of some case studies comparing Mamdani and Sugeno inference systems is presented, mainly from the engineering modeling perspective. These case studies provided the impetus for the present study to investigate a different facet of such comparisons to illuminate some practical aspects of the systems.

2. Case studies

Some case studies of EIA schemes have made use of HFSs as decision support tools. As a case in point, Siqueira Campos Boclin and Mello, (2006) developed an EIA fuzzy decision support system for a highway project in Brazil. They examined four alternative development scenarios, including the "pre-existing situation" and "no action". They created a decision tree which integrates the outputs of fuzzy sub-systems to compute the total environmental situation. All of the subsystems were of the Mamdani type and all of the variables in the model were standardized to the universe of discourse [0, 1]. The membership functions pertaining to the linguistic terms "good", "bad", and "critical" were S-shaped. The defuzzification method was the center of gravity, which generated output values within an interval smaller than in their study [0, 1]; put differently, the final outputs were in the range [0.158, 0.842]. Therefore, the authors added a final normalization step to each subsystem, as well as to the final output, to rescale the outputs at each step to the interval [0, 1]. In this example, the final outputs were converted by subtracting the lower endpoint of the interval (0.158) and dividing the result by the length of the interval.

Likewise, Liu et al., (2009) developed a fuzzy decision support system for an EIA of a Taiwanese high-speed rail project. They divided the project line into three segments and analyzed three different scenarios for each of the segments. They created a hierarchy of Mamdani fuzzy expert systems to assess the impact on environmental criteria and subcriteria. Their model was developed using the Matlab Fuzzy Logic Toolbox. The computed output of each fuzzy expert system was the significance of the associated environmental impact. The universe of discourse relating to all output variables was the interval [0, 100]. Triangular fuzzy membership functions were used for the output variables, with linguistic interpretations ranging from “very insignificant” to “very significant”. The defuzzification method was the center of gravity. The authors reported that the real output range was narrower than the interval [0, 100]. As with the Boclin and Mello (2006) study, Lui et al., (2009) rescaled all intermediate and final outputs so that their lower and upper bounds corresponded to 0.0 and 100, respectively.

It should be mentioned that each higher-ranked system of the hierarchy consisted of two to five sub-systems in both of these models. Studies comparing Mamdani and Sugeno FISs have been carried out in fields other than EIA. For example, Jassbi et al., (2006) compared the performance of Mamdani and Sugeno FISs in detecting generic system faults of the ENVISAT satellite gyroscope. Both FISs were developed to trigger an alarm. The authors observed that, of the two, the Sugeno FIS was much faster, requiring 14 times less processing time. The Sugeno FIS was more robust than its Mamdani counterpart when interpreting noisy data; however, it was also more sensitive to very high noise levels. On this basis, the authors concluded that the Sugeno FIS behaved more realistically than did the Mamdani FIS. Ultimately, they reported that transitions between states were smoother in the Sugeno FIS and that the Sugeno FIS was more sensitive to imprecision where the input fuzzy sets overlapped. Guney and Sarikaya (2009) compared Mamdani and Sugeno FISs for resonant frequency calculation of rectangular microstrip antennas. The designed parameters of both FISs were adjusted using various training algorithms. The absolute errors between the measured resonant frequencies and the frequencies calculated by the FISs were small. However, the best performance was achieved by the Sugeno FIS trained by the least squares algorithm. Özger (2009) compared Mamdani and Sugeno FISs developed to predict stream flow of the Euphrates River in Turkey. Both FISs were trained on the basis of experimental data. The parameters of the Mamdani FIS were adjusted using a genetic algorithm, while the Sugeno FIS was trained using artificial neural networks (ANNs).

In this case, the Mamdani FIS outperformed its Sugeno counterpart in terms of accuracy. However, the performances of both FISs were surpassed by that of a conventional model. Kaur and Kaur (2012) compared Mamdani and Sugeno FISs for the operation of an air conditioning system. In both systems, the input variables were temperature and humidity, and the single output variable was compressor speed. Despite the fact that both systems operated similarly, the air conditioning system worked at full capacity only when using the Sugeno FIS.

3. Material and methods

3.1. Background

This study is a research-oriented, non-commercial EIA based on the data and expertise utilized in a formal EIA study of the South Pars gas pipeline project, Phases 15 and 16. The project area extends from landfall in the vicinity of the coastal village of Assaluyeh to the zone of the platforms of South Pars Deck 15 (Phase 15) and South Pars Deck 16 (Phase 16), approximately 100 km off the southern Iranian coast in the Persian Gulf. The landfall area defined in the program stretches from Kilometer Point (KP) 0.0 to KP 4.7. From KP 4.04 to KP 15.46, the desired pipelines pass through Nayband national Marine Park (Pouyandegan Mohit Zist, 2011). Nayband National Marine Park is one of the most valuable habitats of the Persian Gulf, sheltering coral reefs and marine tortoises.

A prior formal EIA of this project was carried out with a Leopold Matrix (Canter, 1996) with the aim of assessing the environmental impact associated with “action” and “no action” alternatives. The area targeted by the EIA was a 5-km–wide pathway (2.5 km on either side of the pipeline) running through the coastal regions and sea bed (Pouyandegan Mohit Zist, 2011).

3.2. Hierarchical fuzzy systems

In this study, we have developed two HFSs using the same data and expertise that were involved in creating the formal EIA. Our HFSs have been developed with the cooperation of PMZ Company’s experts through brainstorming sessions, using their professional knowledge and the data that were collected for the formal EIA. The conceptual models (Fig. 1 and Fig. 2), fuzzy membership functions (Fig. 3), and all the rule bases (Table 1), are the resultant outputs of such sessions. The present study does not entail public participation or stakeholder views and lies outside the scope of a formal EIA scheme.

We compare the results obtained with a Mamdani FIS-based HFS and a Sugeno FIS-based HFS with identical structures. The input variables are all environmental factors scrutinized in the original EIA. The HFSs are binary systems in which every upper rank FIS consists of two sub-systems, thereby reducing the complexity of the hierarchy and facilitating sensitivity analysis.

3.2.1. Mamdani HFS

The Mamdani HFS (developed with the Matlab R2006b Fuzzy Logic Toolbox) involves the same membership functions for each fuzzy sub-system. All input and output variables are rated in the overlapping fuzzy categories “Poor”, “Mediocre”, and “Good”, reflecting the performance quality of the project for that environmental criterion.

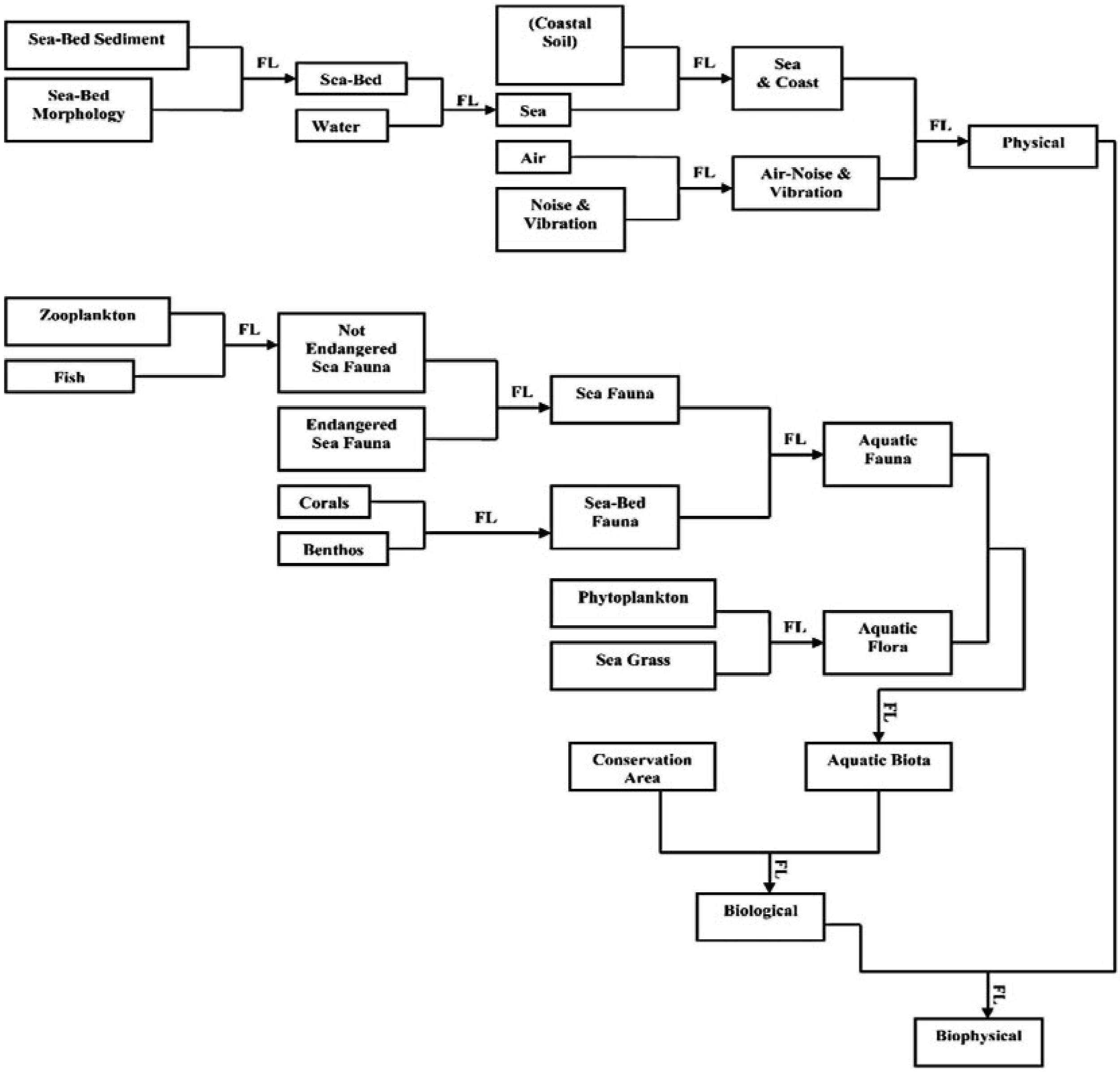

Fig. 1. The conceptual model associated with the Biophysical Index (FL – Fuzzy logic)

Table 1. Fuzzy rules used to calculate the Sea-Bed, Biophysical and Total indices

Rule no.	***If***		***Then***		
	Input1ᵃ is	***And Input 2ᵇ is***	***Sea-Bed is***	***Biophysical is***	***Total is***
1	Poor	Poor	Poor	Poor	Poor
2	Poor	Mediocre	Poor	Poor	Poor
3	Poor	Good	Mediocre	Mediocre	Poor
4	Mediocre	Poor	Mediocre	Poor	Poor
5	Mediocre	Mediocre	Mediocre	Mediocre	Mediocre
6	Mediocre	Good	Mediocre	Good	Good
7	Good	Poor	Mediocre	Mediocre	Poor
8	Good	Mediocre	Good	Good	Mediocre
9	Good	Good	Good	Good	Good

a: Sea-Bed Sediment for the Sea-Bed Index, Physical for the Biophysical Index, and Biophysical for the Total Index; b: Sea-Bed Morphology for the Sea-Bed Index, Biological for the Biophysical Index, and Socio-Economic and Cultural for the Total Index.

The Mamdani and Sugeno HFSs compute project performance indices relating to the environmental components within the interval [0, 1]. The individual indices are integrated in a hierarchical manner to compute the total performance of the project in the order shown in Fig. 1 and 2, respectively. The conceptual models through which the Biophysical and the Total Indices are computed are presented in

Fig. 1. Table 1 shows the rules associated with the Sea-Bed, Biophysical, and Total FISs that typify FISs throughout the hierarchy. The conceptual models through which the Biophysical and the Total Indices are computed are presented in Fig. 2, respectively.

The shapes of the corresponding membership functions are triangular (Fig. 3), and the universe of discourse for all variables is [0, 1].

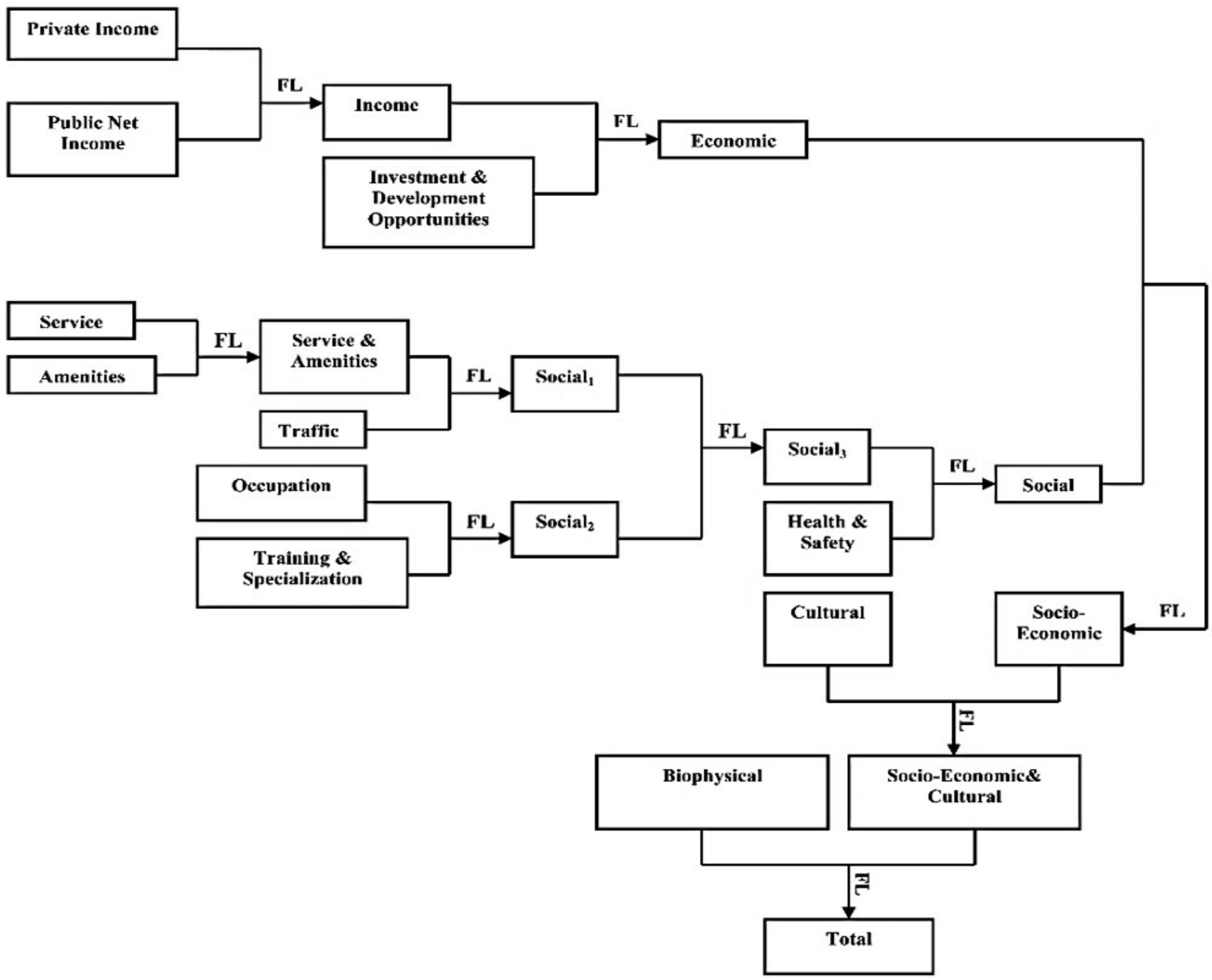

Fig. 2. The conceptual model associated with the Total Index (FL: Fuzzy logic)

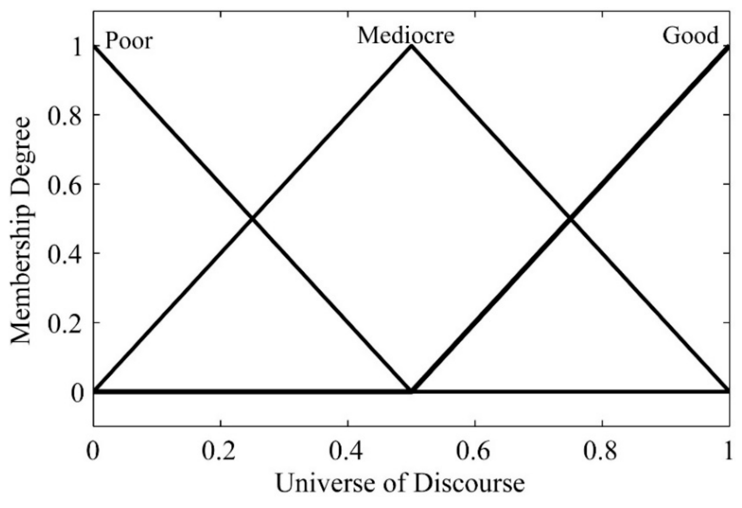

Fig. 3. Fuzzy membership functions

It has to be mentioned that the Sea-Bed and Biophysical FISs represent all FISs, except for the Total FIS, which is a unique FIS throughout the hierarchy. For this study, we use the Centroid defuzzification method. The "AND", implication, and aggregation methods are Minimum, Minimum, and Maximum, respectively.

3.2.2. Sugeno HFS

All the same input variables, input membership functions, and rule bases used for the Mamdani HFSs are used for the Sugeno HFS (developed with the Matlab R2006b Fuzzy Logic Toolbox), in the systems developed for the purpose of this study. In a zero order Sugeno system, the output functions are constants. Here, the "Poor", "Mediocre" and "Good" categories are mapped onto the constants 0.01, 0.5 and 1.0. The selected "AND" method is the Product method.

3.3. Data generation

To generate data, 41 input values ranging from 0.0 to 1.0, with an increment of 0.025, are generated for each input variable. Then, the generated values of both variables are paired in a 41×41 matrix. Eventually, all input pairs generated in this fashion are administered to all FISs of the developed Mamdani and Sugeno HFSs. It is important to mention that, for our purposes, the diagonal simulation means that the corresponding pairs of input values are utilized to generate output values.

Hence, the values of both input variables increase with a 0.025 increment. The row-oriented simulation means that 41 unique values for the first input variable are paired with the 41 unique values of the second input variable in an incremental fashion. Likewise, the column-oriented simulation means that there are 41 unique values for the second input variable, each of them paired with the 41 unique values of the first input variable in an incremental fashion.

3.4. Data analysis

Data analysis is carried out using sensitivity curves, the non-parametric two-related sample Wilcoxon test (Siegel and Castellan, 1998; Statsoft Inc., 2013), linear regression, and by characterizing the variations between adjacent output values. Sensitivity curves are used to observe the general behavior of both HFSs, especially in terms of operating at full capacity. Furthermore, the sensitivity curves are utilized to compare the reliability of HFSs over the full range of possible inputs.

The outputs of the Mamdani FISs are adjusted using the method adopted by Siqueira Campos Boclin and Mello (2006). In the next step, the outputs of the Sugeno FISs are compared with both original and adjusted outputs of the developed Mamdani FISs. The Wilcoxon test is used to detect any significant statistical differences between the outputs of both HFSs.

Linear regression analysis is used to test the linearity of the output function with respect to its input variables. An HFS with linear behavior is equally sensitive to all inputs, producing a balanced scale for comparison. The variation between each pair of adjacent output values is calculated as follows (Eq. 1):

$$\Delta i = i_N - i_{N-1}, \tag{1}$$

where i is the output value and N is the output number

4. Results and discussion

The results of diagonal simulation on the Sea-Bed, Biophysical, and Total FISs are shown in Fig. 4. The shapes of these curves are typical of all sub-systems in the hierarchy.

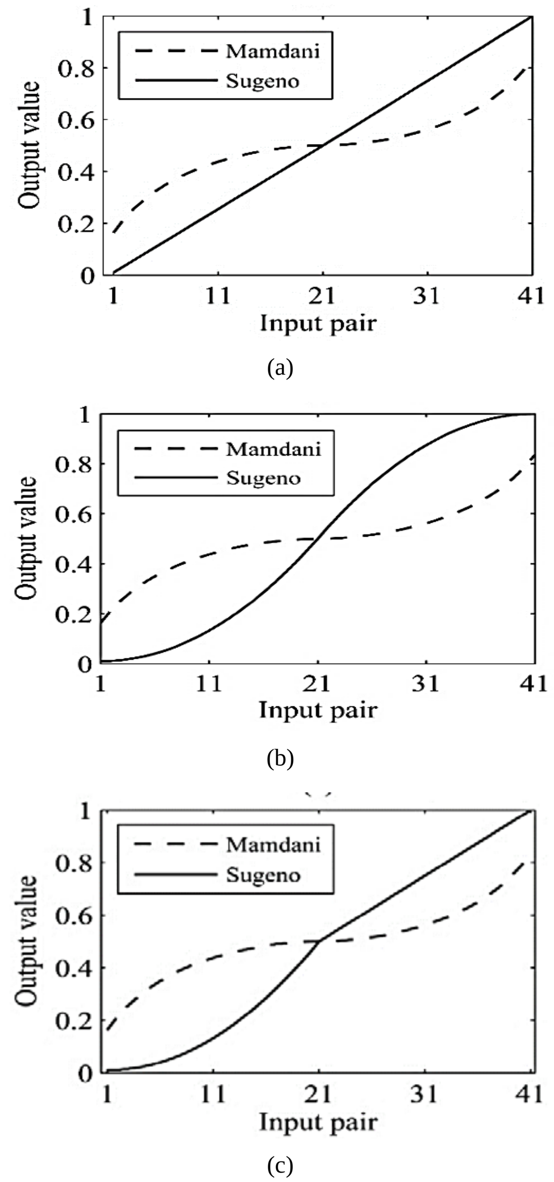

Fig. 4. Results of applying diagonal simulation to the: (a) Sea-Bed FIS; (b) Biophysical FIS and (c) Total FIS.

The Mamdani FISs fail to operate at full capacity, meaning that their output range is narrower than the input range [0, 1], as reported by other authors (Kaur and Kaur, 2012; Liu et al., 2009; Siqueira Campos Boclin and Mello, 2006). To put it in another way, the Mamdani's output range is [0.163, 0.837], indicating the fact that the system is biased toward the end of the interval. This means that the degree of bias (overestimation or underestimation) increases as the inputs move farther from the midpoint. This phenomenon is especially pronounced in comparison with the Sugeno FISs. On the other hand, the Sugeno system operates without any bias toward the endpoints of the interval. Hence, further adjustments have to be made to the Mamdani outputs here, similar to the method adopted by Siqueira Campos Boclin and Mello (2006).

The results of the non-parametric two-related sample Wilcoxon test (Table 2) demonstrate that for the Sea-Bed and Biophysical FISs, there are no statistically significant differences between the output values of the Mamdani (with original or adjusted output values) and Sugeno HFSs ($|Z| < Z_{0.975} = 1.96$; $P > 0.05$; $P_{Montecarlo} > 0.05$). On the other hand, for Total FIS, there are significant statistical differences between the output values of the Mamdani (both with original and adjusted output values) and Sugeno HFSs ($|Z| > Z_{0.975} = 1.96$; $P < 0.05$; $P_{Montecarlo} < 0.05$). This means that, excepting the Total Index results, both HFSs perform similarly in terms of evaluating the performance of decision alternatives with respect to each decision criterion or index. However, with regard to the Total Index, the two HFSs function significantly differently in terms of evaluating the aggregate performance of decision alternatives. Hence, the comparison among the final outputs of the decision alternatives will have a different meaning for each HFS in statistical terms.

Linear regression analysis (Table 3) demonstrates that both the Mamdani (with original or adjusted output values) and Sugeno HFSs are linear at a confidence level of 99% ($P < 0.01$, $F > F_{0.99}(2, 1678) = 4.618$), indicating that the transitions between output values are fairly constant and continuous in both HFSs. In other words, both systems provide a stable measure for drawing comparisons between decision alternatives. Nevertheless, the F and R^2 values associated with the Sugeno HFS are greater than those belonging to the Mamdani HFS, with the original and adjusted output values, indicating that the Sugeno HFS produces more linear behavior, with a higher percentage of points landing on the regression line. Consequently, the Sugeno HFS produces a more balanced scale for comparison.

In addition, the input variables' coefficients for the Sugeno system are greater than those for its Mamdani counterpart. Therefore, any change in the input values will bring about more changes in the output values of the Sugeno system. Hence, besides providing a more balanced scale for comparison, the Sugeno system provides a more sensitive scale for differentiating between decision alternatives, in terms of both decision criteria and aggregate performance.

The percentages of negative variation (Eq. 1) for the original and adjusted versions of the Mamdani HFS are identical.

Table 2. Non-parametric two-related samples Wilcoxon test comparing Mamdani and Sugeno FIS outputs

Compared systems	***FIS***[a]	***Z***[b]	***P***[c]	***P***[d] ***Montecarlo***
Sugeno and Mamdani	***Sea-Bed***	-0.698	0.485	0.482
	Biophysical	-0.773	0.440	0.437
	Total	-16.330	0.000	0.000
Sugeno and Adjusted Mamdani[e]	***Sea-Bed***	-0.874	0.382	0.379
	Biophysical	-0.876	0.387	0.392
	Total	-15.380	0.000	0.000

a: Fuzzy inference system; b: Measure of the test; c: Asymptotic statistical P value (2-tailed); d: Montecarlo statistical P value (2-tailed) "based on 10000 sampled tables; e: With adjusted output values

Table 3. Linear regression analysis results

HFS[a]	***FIS***[b]	***Coefficients***			***R²***	***F***[e]	***P***[f]
		Input1[c]	***Input2***[d]	***Constant***			
Original Mamdani [g]	***Sea-Bed***	0.305	0.103	0.296	0.788	3.118exp3	<0.01
	Biophysical	0.311	0.311	0.189	0.874	5.831exp3	<0.01
	Total	0.216	0.319	0.184	0.682	1.802exp3	<0.01
Adjusted Mamdani[h]	***Sea-Bed***	0.453	0.153	0.197	0.788	3.118exp3	<0.01
	Biophysical	0.462	0.462	0.038	0.874	5.831exp3	<0.01
	Total	0.320	0.474	0.030	0.682	1.802exp3	<0.01
Sugeno	***Sea-Bed***	0.736	0.254	0.007	0.934	1.184exp4	<0.01
	Biophysical	0.736	0.736	-0.233	0.962	2.118exp4	<0.01
	Total	0.493	0.736	-0.238	0.824	3.920exp3	<0.01

a: Hierarchical fuzzy system; b: Fuzzy Inference System; c: Sea-Bed Sediment for the Sea-Bed FIS, Physical for the Biophysical FIS, and Biophysical for the Total FIS; d: Sea-Bed Morphology for the Sea-Bed FIS, Biological for the Biophysical FIS, and Socio-Economic and Cultural for the Total FIS; e: Fisher Test Critical Value; f: Statistical P value; g: With original output values; h: With adjusted output values

Negative variations are symptomatic of fluctuations in the output surface. On the contrary, this phenomenon is not observed with the Sugeno FISs. Rather, in the corresponding areas of the Sugeno HFS, the slope of change decreases (Fig. 5) or remains constant (Fig. 6). Notice in Table 4 that, in most cases, negative variations happen where the constant variable values are within the extreme ranges of [0.0, 0.25] and [0.75, 1]. Moreover, it can be inferred that when an input variable with a higher coefficient is held constant (Table 3), the variation of the other variable's values spreads the mentioned error into other constant variable value ranges, with the central value being maintained (i.e. 0.5).

When the first input variable (i.e. Physical Index) is held constant at 0.85 and paired with all values related to the second input variable (i.e. Biological Index) ranging from 0 to 1 with an increment of 0.025 (Fig. 5), the slope of variation for the Sugeno FIS increases from point 21 onward. On the other hand, the output values for the Mamdani FIS (original and adjusted output values) are constant from point 21 to 27, followed by conspicuous fluctuating pattern in the curve associated with the output values.

When the second input variable (i.e. Socio-Economic and Cultural Index) is held constant at 0.950 and paired with all values of the first input variable (i.e. Biophysical Index), ranging from 0 to 1 with an increment of 0.025, the Sugeno output values increase at a constant rate of 0.047 between points 1 and 21 and then level out (Fig. 6 and Table 5). On the other hand, in the Mamdani FIS, with both original and adjusted output values, the output values increase at a varying rate between points 1 and 21 and fluctuate thereafter between two identical values. These findings provide a practical explanation for the linear regression results (Table 3) while underscoring the fact that the Sugeno system provides a more balanced scale for comparison than its Mamdani counterpart. Between points 1 and 21, the outputs of the Sugeno system react more sensitively to changes in the input variable values (Table 5). This phenomenon provides another practical explanation for the linear regression results (Table 3), demonstrating that the Sugeno system provides a more sensitive scale for comparison than its Mamdani counterpart.

From the data shown in Fig. 6 and Table 5, it can be inferred that in the fluctuating areas between points 21 and 41, the Mamdani system fails to live up to the expectation that when one input variable is held constant, the response to increases in the other input should be monotonic. In other words, this phenomenon is construed as pseudo-sensitivity and may distort differentiation between alternatives in terms of decision criteria or aggregate performance. For example, assume that we have two schemes respectively named alternative 1 and 2 with an identical Socio-Economic and Cultural input value of 0.95 using the Mamdani Total FIS with the original output values for computation. The biophysical scores of the two alternatives are 0.650 and 0.675, respectively. According to the rule base (Table 1), one could expect logically that alternative 2 would match or surpass the Total Index score of alternative 1. However, the computed Total scores associated with alternative 1 and 2 are 0.73 and 0.72, respectively, defying logic.

Table 4. Percentage of negative variation cases related to Mamdani FISs

Simulation type	***FIS***[a]	***Constant variable values***				
		[0.0, 0.25]	[0.275, 0.475]	0.5	[0.525, 0.725]	[0.750, 1.0]
Row-Oriented [b]	***Sea-Bed***	12.5%	21.1%	0.0%	21.1%	12.5%
	Biophysical	12.5%	0.0%	0.0%	0.0%	12.5%
	Total	35.2%	0.0%	0.0%	0.0%	0.0%
Column-Oriented [c]	***Sea-bed***	8.6%	0.0%	0.0%	0.0%	8.6%
	Biophysical	12.5%	0.0%	0.0%	0.0%	12.5%
	Total	25.0%	10.6%	0.0%	10.6%	12.5%

a: Fuzzy inference system; b: Each unique value of the first variable, the constant variable, is paired with all unique values of the second variable; first input variables are Sea-Bed Sediment for the Sea-Bed FIS, Physical for the Biophysical FIS, and Biophysical for the Total FIS; c: Each unique value of the second variable, the constant variable, is paired with all unique values of the first variable; second input variables are Sea-Bed Morphology for the Sea-Bed FIS, Biological for the Biophysical FIS, and Socio-Economic and Cultural for the Total FIS

Table 5. Variation values associated with results shown in Fig. 6

Type of fuzzy inference system	***Input pair range***					
	1−21			21−41		
	Min[a]	***Max***[b]	***Mean***	***Min***	***Max***	***Mean***
Original Mamdani[c]	0.0022	0.0542	0.0289	-0.0089	0.0089	0
Adjusted Mamdani[d]	0.0033	0.0805	0.0428	-0.0132	0.0132	0
Sugeno	0.0470	0.0470	0.0470	0	0	0

a: Minimum; b: Maximum; c: With original output values; d: With adjusted output values

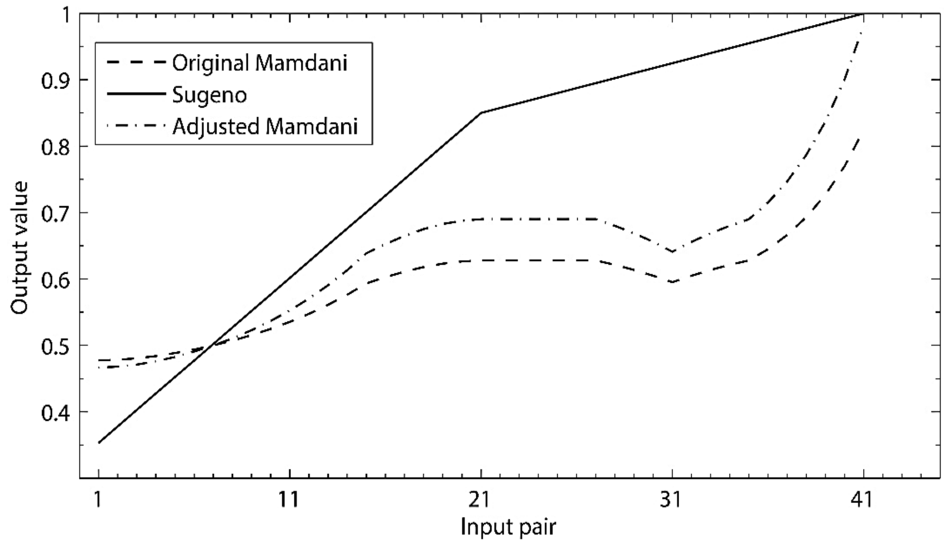

Fig. 5. Results for one row of row-oriented simulation for the Mamdani and Sugeno Biophysical FISs

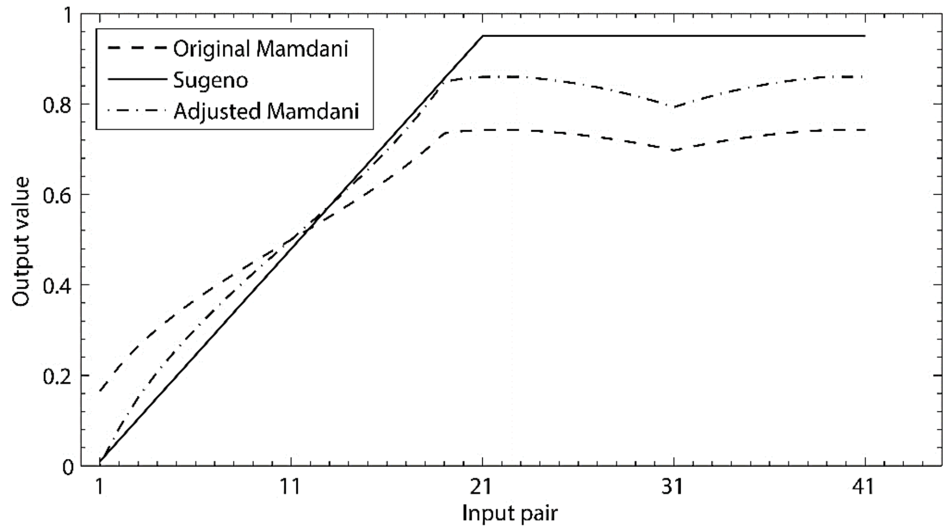

Fig. 6. One column of the column-oriented simulation results for the Mamdani and Sugeno Total FISs

In contrast, the Sugeno HFS is reliable over the entire curve. When using the Mamdani HFS, it is necessary to take into account such areas of fluctuation so as to prevent any misinterpretation. One way to tackle such problems is to use smoothing techniques. For example, the fluctuated area of the total Mamdani FIS can be smoothed into a shape similar to the corresponding area of the Sugeno Total FIS by applying the linear interpolation method (Fig. 6).

5. Conclusions

This study compares Mamdani and Sugeno HFSs in the context of a non-commercial research-oriented EIA case study of a pipeline project in southern Iran from a multi-criteria decision analysis perspective. The developed HFSs are binary systems that reduce complexity and facilitate sensitivity analysis. The study aim is to provide insight into practical aspects of the developed systems through their comparison and thereby produce results that are useful to consider during application. The developed systems have the potential to be expanded, revised, validated, and utilized in other EIA studies of similar projects in the region.

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