An Application of Fuzzy Logic to Strategic Environmental Assessment

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Abstract. Strategic Environmental Assessment (SEA) is used to evaluate the environmental effects of regional plans and programs. SEA expresses dependencies between plan activities (infrastructures, plants, resource extractions, buildings, etc.) and environmental pressures, and between these and environmental receptors. In this paper we employ fuzzy logic and many-valued logics together with numeric transformations for performing SEA. In particular, we discuss four models that capture alternative interpretations of the dependencies, combining quantitative and qualitative information. We have tested the four models and presented the results to the expert for validation. The interpretability of the results of the models was appreciated by the expert that liked in particular those models returning a possibility distribution in place of a crisp result.

1 Introduction

Regional planning is the science of the efficient placement of land use activities and infrastructures for the sustainable growth of a region. Regional plans are classified into types, such as agriculture, forest, fishing, energy, industry, transport, waste, water, telecommunication, tourism, urban and environmental plans to name a few. Each plan defines activities that should be carried out during the plan implementation. Regional plans need to be assessed under the Strategic Environmental Assessment (SEA) directive, a legally enforced procedure aimed at introducing systematic evaluation of the environmental effects of plans and programs. This procedure identifies dependencies between plan activities (infrastructures, plants, resource extractions, buildings, etc.) and positive and negative environmental pressures, and dependencies between these pressures and environmental receptors.

[3] proposed two logic based methods to support environmental experts in assessing a regional plan: one based on constraint logic programming and one based on probabilistic logic programming. Both methods translate qualitative dependencies into quantitative parameters (interpreted in the first model as linear

coefficients and in the second as probabilities). However, transforming qualitative elements into numbers without a proper normalization runs the risk of summing non homogeneous terms. In addition, not all impacts should be aggregated in the same way: some pressures may indeed be summed, some receptors present a saturation after a given threshold, while for others a different combination is required in case of positive and negative synergies between activities or between pressures.

To deal with qualitative information, we employ fuzzy logic, a form of multi-valued logic that is robust and approximate rather than brittle and exact. We propose four alternative models. The first model modifies the linear one (i.e., the one implemented via the constraint programming approach) in terms of quantitative fuzzy concepts. The second model is a qualitative interpretation of the dependencies exploiting many-valued logics and gradual rules. The third and the fourth are variants of more traditional fuzzy models that use fuzzy partitions of the domains of variables and provide a semi-declarative definition of the relations using fuzzy rules. All the models are parametric in the definition of the combination operators.

We consider as a case study the assessment of Emilia Romagna regional plans. We describe specific experiments on the regional energy plan explaining the strength and weakness of each model. The models have been extensively tested and the results have been proposed to environmental experts, who appreciated in particular the fourth model, combining linear and fuzzy logic features, guaranteeing high expressiveness and proposing results in a very informative way.

2 Strategic Environmental Assessment

Regions are local authorities that include among their tasks the planning of interventions and infrastructures. Particular emphasis is devoted to energy, industry, environment and land use planning. Before any implementation, regional plans have to be environmentally assessed, under the *Strategic Environmental Assessment Directive*. SEA is a method for incorporating environmental considerations into policies, plans and programs that is prescribed by EU policy.

In the Emilia Romagna region the SEA is performed by applying the so-called *coaxial matrices*, that are a development of the network method [7]. The first matrix defines the dependencies between the activities contained in a plan and positive and negative pressures on the environment. The dependency can be *high*, *medium*, *low* or *null*. Examples of negative pressures are energy, water and land consumption, variation of water flows, water and air pollution and so on. Examples of positive pressures are reduction of water/air pollution, reduction of greenhouse gas emission, reduction of noise, natural resource saving, creation of new ecosystems and so on. The second matrix defines how the pressures influence environmental receptors. Again the dependency can be *high*, *medium*, *low* or *null*. Examples of environmental receptors are the quality of surface water and groundwater, quality of landscapes, energy availability, wildlife wellness and so on. The matrices currently used in Emilia Romagna contain 93 activities, 29 negative pressures, 19 positive pressures and 23 receptors.

The SEA is now manually performed by environmental experts on a given plan. A plan defines the so-called *magnitude* of each activity: magnitudes are real values that intuitively express *"how much"* of an activity is performed with respect to the quantity available in the region. They are a percentage for each activity.

3 Fuzzy and Many-Valued Logic

After the introduction of the concept of fuzzy set [9] by Zadeh for modeling vague knowledge and partial degrees of truth, much work has been done in various research areas to apply the concept of fuzziness to existing fields, including formal logic. Historically, two possible approaches have been adopted [5]: one, more mathematically oriented, belongs to the family of many-valued logics and is called fuzzy logic "in a narrow sense", while the other, fuzzy logic "in a broader sense", is closer to Zadeh's original definition and uses a softer approach.

"Fuzzy" many-valued logics are a truth-functional generalization of classical logic. Atomic predicates p/n are considered fuzzy relations, whose truth degree is given by their associated membership function μ_P. Thus predicates can have truth values in the range $L = [0, 1]$. In order to construct and evaluate complex formulas, logical connectives, quantifiers and inference rules (e.g. modus ponens) are generalized to combine truth degrees. For example, the conjunction operator can be defined using any *t-norm* $\star$, such as the minimum, the product or Łukasiewicz's norm. Likewise, the disjunctive connective is defined using an *s-norm* and the implication depends on the t-norm definition by residuation [4]. A rule $C \leftarrow_i A$, then, can be used to entail a fact C with a degree of at least c, provided that a fact matching with A exists with degree $a > 0$ and that the implication $\leftarrow$ itself has a degree $i > 0$.

In [9], Zadeh introduced the concept of *fuzzy linguistic variable*, a qualitative construct suitable to describe the value of a quantitative variable X with domain Δ_X. Each linguistic value λ_j belongs to a finite domain Λ and is associated to a fuzzy set A_j. Together, the sets define a fuzzy partition of Δ_X iff $\forall x \in \Delta_X$: $\sum_j \mu_{A_j}(x) = 1$. The membership values of an element x to a set can either be interpreted as the *compatibility* of x with the concept expressed by a linguistic variable, or as the *possibility* that x is the actual value of X, assuming that x is unknown save for the fact that it belongs to A_j. (For a complete discussion on the relation between compatibility and possibility, see [2]).

Fuzzy partitions are usually used in conjunction with fuzzy rules to approximate complex functions $y = f(x)$ by fuzzifying the function's domain and range, then matching the resulting input and output sets using rules [1]. Different types of rules have been proposed: "Mamdani" rules infer fuzzy consequences from fuzzy premises and have the form $x \textit{ is } A_j \;\Rightarrow_\varepsilon\; y \textit{ is } B_k$[4]; Fuzzy Additive Systems (FAS), instead, entail quantitative values. In the former case, then, it is

[4] A_j and B_k are fuzzy sets and *is* is the operator evlauating set membership.

necessary to collect the different sets entailed by the various rules, combine them - usually by set union - into a single possibility distribution and finally, if appropriate, apply a defuzzification process [6] to get a crisp consequence value. In the latter case, instead, the quantitative values are directly available and can be aggregated, e.g., using a linear combination.

4 Models

[3] proposed two logic-based approaches for the assessment of environmental plans. The first, based on Constraint Logic Programming on Real numbers (CLP($\mathcal{R}$)), interprets the coaxial matrix qualitative values as coefficients of linear equations. The values, suggested by an environmental expert, were 0.25 for *low*, 0.5 for *medium*, and 0.75 for *high*. The advantages of such a model are its simplicity, efficiency and scalability, but, due to its linearity, it assumes that positive and negative pressures derived from planned activities can be always summed. While, in general, pressures can indeed be summed, in some cases a mere summation is not the most realistic relation and more sophisticated combinations should be considered.

The second, based on Causal Probabilistic Logic Programming, gave a probabilistic interpretation to the matrices. The same numeric coefficients have been used to define the likelihood of a given pressure (or receptor) being affected by an activity (respectively, a pressure). While probability laws allow for a different combination strategy, the relations used by the experts are vague and they have a gradual nature rather than a stochastic one: how an activity (respectively a pressure), when present, affects a pressure (respectively receptor) is usually a matter of degree of truth/possibility and not of chance.

The purpose of this paper, then, is to provide alternative models of the dependencies, exploiting the concepts and mechanisms of Multi-Valued Logic and Fuzzy Logic. The first step in formalizing the required concepts is to redefine the involved variables (such as activities' magnitude, pressures and environmental receptors) in terms of fuzzy sets and linguistic variables.

There are two main approaches for representing each variable (activity, pressure or receptor) in our model. The first is to define a many-valued predicate, $mag/1$, whose truth value represents the magnitude of that variable, i.e. represents how much the considered variable is "large" in terms of a truth value in the interval $[0, 1]$. Notice that, although the predicate is the same, the membership function is different for each variable. For example, if we have the activity *road construction* and atom $mag(road)$ has truth value 0.7, this means that the plan involves the building of a significant amount (0.7) of roads with respect to the current situation, while a smaller truth value would correspond to a smaller number of kilometers of roads to be built.

In the second approach, a fuzzy linguistic variable is defined for each variable, creating a fuzzy partition on its domain. The partition contains one fuzzy set for each value of the linguistic variable. The sets are used to describe different levels of magnitude: we consider a five-set fuzzy partition of each variable's domain consisting of the sets *VeryLow*, *Low*, *Average*, *High* and *VeryHigh*.

The second degree of freedom we have is the selection of the aggregation method for the results, i.e. the choice of the s-norm used to combine the results of the application of rules with the same consequent. For example, consider two pressures such as energy consumption and odor production; the overall energy consumption is the sum of the consumptions due to the single activities, but the same hardly applies to odor production. An activity that produces a strong odor may "cover" weaker odors, so a good aggregation for this kind of variable should be the maximum (or geometrical sum). The aggregation strategy becomes even more important in the case of environmental receptors.

Pressures can be either "positive" or "negative": translating positive pressures into positive contributions, and negative ones into negative contributions would be an approximation since the former do not always cancel the latter. If a linear model returns a final result of 0 for a given receptor, there is no way of telling whether that value is the combination of large positive and negative contributions canceling each other, or we are simply in the case of absence of significant pressures influencing that receptor. So, we have chosen to split the individual receptor variables into two parts, one considering only positive and one considering only negative pressures affecting that receptor. The strategy for the combination of the two can then be decided on an individual basis.

In the remainder of this section, we will provide a description of the four classes of models which can be designed, according to different combinations of the underlying logic (many-valued vs classical fuzzy) and aggregation style (linear vs non-linear).

4.1 Many-valued logic models

Model I. To begin with, we revised the existing constraint based model in terms of quantitative fuzzy concepts. The original formulation [3] takes as input the activities, in terms of their relative magnitudes, and calculates pressures as $p_j = \sum_{i=1}^{N_a} m_{ij} * a_i$. Each coefficient m_{ij} quantifies the dependency between the activity i and the pressure j according to the qualitative value in the matrix M. The values $a_{i:1..N_a}$, instead, are the magnitudes of each activity: the values represent the increment of an activity A_i as a percentage in relation to the existing A_i^0, in order to make the different activities comparable. For example, a magnitude of 0.1 for activity *"thermoelectric plants"* means increasing the production of electricity through thermoelectric energy by 10% with respect to the current situation.

Likewise, the influence on the environmental receptor r_k is estimated given the vector of environmental pressures $p_{j:1..N_p}$ calculated in the previous step. An alternative formulation of the model, this time in logic terms, is composed by the following Horn clauses:

$$contr(Press_j, Act_i) \Leftarrow_{\beta_{i,j}} mag(Act_i) \wedge impacts(Act_i, Press_j) \qquad (1)$$

$$mag(Press_j) \;\Leftarrow_1\; \exists\, Act_i : contr(Press_j, Act_i) \tag{2}$$

where we use the auxiliary predicate *contr* to describe the contribution from a single source, whereas *mag* describes the aggregate contributions.

	Lin.	**Non Lin.**
MVL	Model I	Model II
Fuzzy	Model IV	Model III

Fig. 1. Model classification by type of logic and aggregation style.

The value $\beta_{i,j}$ is a normalization coefficient, that makes the maximum possible value of truth for $mag(Press_j)$ equal to 1 when the truth degree of $mag(Act_i)$ for all the impacting activities is equal to 1. Its default value can be changed by the environmental expert to obtain other behaviors.

In order to replicate the behavior of the linear model, we need to (i) configure the $mag/1$ predicate to use a linear membership function, (ii) configure the $impacts/2$ predicate to use a membership function derived directly from the matrix, i.e. $\mu_{impacts(Act_i,Press_j)} = m_{ij}$ where m_{ij} is the real value obtained from the qualitative dependencies as in [3] , (iii) configure the $\wedge$ operator to use the product t-norm, (iv) configure the $\exists$ quantifier to use a linear combination s-norm and (v) configure the reasoner to use gradual implications and the product t-norm to implement modus ponens.

The critical point is that the logic operators do not aggregate values, which have only a quantitative interpretation, but degrees of truth, which have a more qualitative interpretation. If one wants the degree to be proportional to the underlying quantitative value, the use of scaling coefficients might be mandatory since a degree, having an underlying logic semantics, is constrained in $[0, 1]$. Intuitively, the coefficients model the fact that, even if an individual piece of evidence is true, the overall proof may not: the coefficient, then, measures the loss in passing from one concept to the other (which, from a logical point of view, is a gradual implication). If the coefficients are chosen accurately, the aggregate degree becomes fully true only when all the possible contributions are fully true themselves. As a side effect, the normalization function used by the predicate $mag/1$ cannot map the existing amount A_i^0 of a given activity to 1, since that is not the theoretical maximum of a new activity, and the contributions of the individual activities require a scaling by a factor $\beta_{i,j}$ before being aggregated.

Model II. After a more detailed discussion with the expert, however, it turned out that no single model alone — qualitative or quantitative, linear or non-linear — could capture the full complexity of the problem, mainly because the relations between the entities are different depending on the actual entities themselves.

A purely linear model has also other limitations: for example, some public works are already well consolidated in the Emilia Romagna region (e.g. roads), so that even a large scale work would return a (linearly) normalized activity value around 1. Others, instead, are relatively new and not well developed (e.g. wind plants), so even a small actual amount of work could yield a normalized value of $5 \div 10$, unsuitable for logic modelling as well as being unrealistic given the original intentions of the experts. In order to cope with this problem, we decided to adopt a non-linear mapping between the amount of each activity and its equivalent value, using a sigmoid function:

$$a_i = \frac{1 - e^{-A_i/(k_i A_i^0)}}{1 + e^{-A_i/(k_i A_i^0)}} \tag{3}$$

This expression behaves like a linear function for small relative magnitudes, while saturates for larger values, not exceeding 1. The relative magnitude can be further scaled using the parameter k_i, provided by the expert, to adjust the behaviour for different types of activities. Moreover, the normalization function (3) is a proper membership function for the fuzzy predicate $mag/1$, defining how large the scale of an activity is with respect to the existing and using the parameter k_i to differentiate the various entities involved.

This membership function, however, also slightly changes the semantics of the linear combination. In the original linear model, we had a sum of quantitative elements, measured in activity-equivalent units and weighted by the coefficients derived from the matrix, and we tried to replicate the same concept in Model I. Now, instead, we have a proper fuzzy count of the number of activities which are, at the same time, "large" and "impacting" on a given pressure. Notice, however, that we still need gradual implications, in order to use the standard, "*or*"-based existential quantifier to aggregate the different contributions.

The second extension we introduce in this model involves the relation between pressures and receptors. While in Model I it is sufficient to replicate rules (1) and (2), here we keep the positive and negative influences separated:

$$\begin{aligned}
contrPos(Press_j, Rec_k) &\Leftarrow_{\gamma_{j,k}} mag(Press_j) \wedge impactsPos(Press_j, Rec_k)\\
contrNeg(Press_j, Rec_k) &\Leftarrow_{\delta_{j,k}} mag(Press_j) \wedge impactsNeg(Press_j, Rec_k)\\
influencePos(Rec_k) &\Leftarrow_1 \exists\, Press_j : contrPos(Press_j, Rec_k)\\
influenceNeg(Rec_k) &\Leftarrow_1 \exists\, Press_j : contrNeg(Press_j, Rec_k)
\end{aligned}$$

In order to combine the positive and negative influences, their relation has to be expressed explicitly. For example, rule (4) states that positive and negative influences are interactive and affect each other directly; rule (5) defines the concept of beneficial pressures explicitly, while rule (6) stresses those receptor which have been impacted in an absolute way. As usual, the operator definitions can be chosen on a case-by-case basis to better model the relations between the particular pressures and receptors.

$$influencePos(Rec_k) \Leftrightarrow_\varepsilon \neg\ influenceNeg(Rec_k) \quad (4)$$

$$benefit(Rec_k) \Leftarrow_1 influencePos(Rec_k) \wedge \neg\ \ influenceNeg(Rec_k) \quad (5)$$

$$hit(Rec_k) \Leftarrow_1 influencePos(Rec_k) \vee influenceNeg(Rec_k) \quad (6)$$

4.2 Fuzzy Models

In models I and II, the elements of the coaxial matrices are converted into simple scaling coefficients. To increase the expressiveness of this mapping, we assumed that each label is actually an indicator for some kind of predefined function, for which we do not provide an analytic expression, but a fuzzy logic approximation [1]. So, we created fuzzy partitions on the domain of each activity, pressure and receptor: in particular, each partition consists of 5 triangular membership functions, not necessarily equally spaced on the domains. These sets have been associated to the linguistic values *VeryLow*, *Low*, *Average*, *High* and *VeryHigh*. Then, we used rules such as $VeryLow(Act) \Rightarrow VeryLow(Pres)$ to map (linguistic) values from one domain onto (linguistic) values of the corresponding range, according to the connections expressed in the matrices.

In both model III and IV we gave the same interpretation to the matrix elements, using linear functions with slope 1, 0.5 and 0.25 for "*high*", "*medium*" and "*low*" respectively. These functions, then, have been fuzzified as shown schematically in Figure 2. A *VeryHigh* input is mapped onto a *VeryHigh*, *Average* or *Low* output, respectively, when the label in a cell of a coaxial matrix is *high*, *medium* or *low*. The mapping can easily be changed by altering the rules and allows to define non-linear relations as well as linear ones. In fact, the use of a fuzzy approximation gives a higher flexibility to the system, while keeping the evaluation robust.

Model III and IV. Model III is a canonical fuzzy system, where the relations between (i) activities and pressures and (ii) pressures and positive and negative effects on receptors are defined using fuzzy rules. The inputs, the activities' magnitudes, are no longer normalized, but fuzzified: the rules are then evaluated using the min-max composition principle [1] and chained, propagating the inferred fuzzy distributions from the pressures onto the receptors. If needed, the resulting possibility distributions can then be defuzzified to obtain a crisp "impact" value for each receptor. Using this model, it is possible to distinguish pressures which are affected by the different activities at different levels.

According to the experts, however, this model suffers from a drawback: being purely qualitative, the degrees inferred for each fuzzy set tell only whether a pressure/receptor will *possibly* be affected with any level of intensity. Suppose for example that activity a_i generates pressure p_j with *Low* intensity. If the magnitude of a_i is sufficiently large, the system will entail that it is (fully) possible that p_j has a *Low* component. This answer is not quantitative: it would not allow to distinguish this case from one where many different activities, all individually generating pressure p_j with low intensity, are present at the same time. Thus, this model is appropriate when only a qualitative answer is sufficient.

To overcome this limitation, we created Model IV as a minor extension of Model III, exploiting the same concepts used in Model II. We used gradual rules to scale and give an additional quantitative meaning to the consequence degrees: $VeryLow(Act) \Rightarrow_\beta VeryLow(Pres)$. Then, we allowed the norms to be configurable, so the min-max composition principle was replaced by a more general t-s norm composition principle. The min-max model, now a special case, is still admissible and is suitable for situations where the various inputs are not interactive, whereas the probabilistic sum and the algebraic sum s-norms are more suitable when the sources are independent or exclusive.

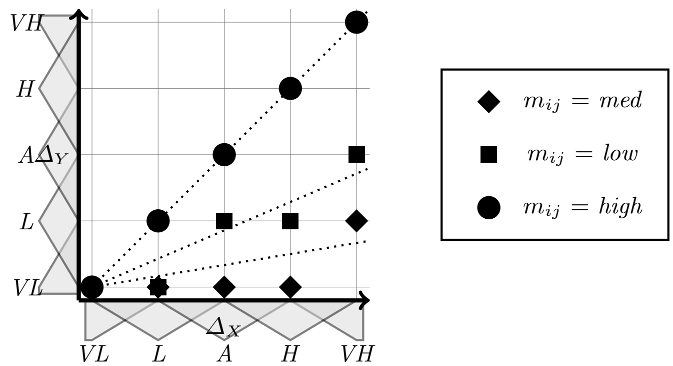

Fig. 2. Relation between an activity a_i and a pressure p_j depending on the value m_{ij} appearing in the coaxial matrix.

5 Model Evaluation

We implemented the four models using the Jefis Library [8], and tested the software on a system equipped with a Core 2 Duo T6600 processor and 4GB RAM. Using the full content of the coaxial matrices to derive the rules and a past regional energy plan as a realistic test case, the evaluation required less than 1 second, guaranteeing that computation time is not a critical factor for the proposed system, considering also that the task is not to be performed in hard real time. Instead, we focus on the assessment of the expressiveness of the four models. Here, due to space limitations and for the sake of readability, we will discuss a more focused test case rather than a whole plan.

We assume that the matrices contain only two activities - *Incinerators* (INC) and *Wastewater Treatment Plants* (WTP), two pressures - *Noxious Gases Emission* (NG) and *Odor Emission* (OD), and one environmental receptor - *Landscape Quality* (LQ). In our example, the two activities influence both pressures, albeit in a different way. The first pressure, NG, is assumed to be linear in the causes: different independent sources simply increase the amount of gas released

		NG	OD
Act	INC	*H*	*M*
	WTP	*M*	*H*
Rec	LQ	*L*	*H*

Table 1. Excerpt of the Coaxial Matrices

into the atmosphere; the latter, OD, is not linear: since odors cover each other, we assumed the sources to be independent but interactive. Moreover, both pressures affect negatively the considered receptor, with an influence strength shown by the matrix excerpt in Table 1. When computing the effects of the pressures, instead, we assumed them to be independent and non-interactive, so the positive (respectively, negative) impact on the receptor is given by the best (resp. worst) effect induced by a pressure. Notice that only models II and IV are able to capture these differences, since model I is linear by default, and model III is non-interactive by default. Given this simplified matrix, the models were set up as follows. Regarding activities, we assume that the initial input is already expressed in terms of equivalent units: a planned magnitude of 100 units is equivalent to the currently existing amount of the same activity. In our test, we set $A_{INC} = 90$ and $A_{WTP} = 180$.

To perform a linear normalization in Model I, we assume that plans cannot involve values greater than 200, effectively planning the construction of no more than twice the existing. When the sigmoidal normalization is used in Model II, an upper limit is not necessary; however, for comparison purposes, we chose values for k_{INC} and k_{WTP} such that the result is the same as when the linear normalization is applied, i.e. the resulting normalized values are 0.45 and 0.9 respectively. Models III and IV, instead, do not require an explicit normalization, since it is performed implicitly by the fuzzification of the magnitudes. Since they are already expressed in equivalent units, all activities share the same domain - the range [0..200], which has been partitioned using sets labelled *VL*, *L*, *A*, *H* and *VH*. All sets are uniformly spaced and use triangular membership functions, except *VH*, which uses a "right-shoulder" function, and *VL*, which uses a "left-shoulder" function. As already pointed out, in Model I and II the values of both matrices are mapped onto 0.75, 0.5 and 0.25; Model III and IV, instead, map the values onto different set of rules, as shown in figure 2. When evaluating the pressure NG, Model II and IV also use scaling coefficients $\beta = 0.5$ (i.e. the reciprocal of the number of activities) to avoid saturation.

We now discuss the evaluation of the different models. First, we consider the relation between INC, planned with magnitude 90, and NG, which is *high* according to the matrix.

I Using rule (1) with the product norm, the linearly normalized magnitude, 0.45, is scaled by the coefficient 0.75, yielding a contribution of 0.3375.

II Similarly, the sigmoidal normalization yields 0.45. This time, however, the gradual rule entails a pressure magnitude of 0.16875.

III The fuzzification of the input yields a reshaped partition $\{L/0.75, A/0.25\}$ describing the magnitude of the activity. After the adequate set of rules has been applied, one obtains a contribution for the distribution of the pressure, which incidentally is identical: $\{L/0.75, A/0.25\}$.

IV The result is analogous in Model IV, save for the effect of the gradual rule: $\{L/0.375, A/0.125\}$

In order to compute the overall degrees for the pressure NG, one must also take into account the contributions due to the WTP activity, planned with magnitude 180: according to the coaxial matrix, the relation between the two is *medium*.

I The second contribution, 0.9, is summed to the previous one, yielding 0.7875.

II This model gives a contribution of 0.225. Depending on the chosen s-norm, this value is combined with the other value of 0.16875: since gas emissions are additive, we use Łukasiewicz's *or* to get a combined value of 0.39375.

III The fuzzified input, $\{H/0.5$, $VH/0.5\}$, is mapped onto the output as $\{L/0.5$, $A/0.5\}$ due to the use of a different set of rules, in turn due to the relation between the two being defined as *medium*. The fuzzy union of the previous and current contributions gives $\{L/0.75, A/0.5\}$.

IV The combination of gradual fuzzy rules, and the use of Łukasiewicz's *or* leads to a final result of $\{L/(0.375 + 0.25), A/(0.125 + 0.25)\}$

The same procedure is repeated for OD. Notice that, due to the initial modelling assumptions, a more appropriate s-norm for models II and IV is the "probabilistic sum". Once both pressures have been evaluated, the inference propagation pattern is applied once more to obtain the final degree/distribution for the receptor LQ. Given the initial assumption of non-interactivity, the "max" s-norm would be more appropriate in models II and IV, however we performed the computations also using the bounded and noisy sum norms for comparison. All the intermediate and final results are reported in table 2. Notice that we only consider negative effects on the environmental receptor because all pressures considered in this example were considered as negative pressures.

6 Conclusions

In this paper we proposed a fuzzy logic approach to SEA. We implemented four models, with different features and informative capabilities. Model I is an implementation of a linear model in fuzzy logic; it cannot distinguish interactive from non-interactive effects, and scenarios with many small effects from scenarios with a few large ones. Model II can cope with the former problem, but not with the latter, while Model III tackles the latter but not the former. Model IV combines the two aspects in a single model and was considered by the expert as the most expressive and informative. Moreover, instead of an unrealistically

		I	II	III	IV
Act	INC	0.45	0.45	$\{L/0.75, A/0.25\}$	$\{L/0.75, A/0.25\}$
	WWTP	0.90	0.90	$\{H/0.5, VH/0.5\}$	$\{H/0.5, VH/0.5\}$
Press	NG	0.79	0.39	$\{L/0.75, A/0.5\}$	$\{L/0.625, A/0.375\}$
	OD	0.90	0.72	$\{VL/0.75, L/0.25, H/0.5, VH/0.5\}$	$\{VL/0.75, L/0.25, H/0.5, VH/0.5\}$
Rec	$LQ_{\vee}^{-}$	0.87	0.54	$\{VL/0.75, L/0.25, H/0.5, VH/0.5\}$	$\{VL/0.75, L/0.25, H/0.5, VH/0.5\}$
	LQ_{+}^{-}	0.87	0.64	$\{VL/0.75, L/0.25, H/0.5, VH/0.5\}$	$\{VL/1.00, L/0.25, H/0.5, VH/0.5\}$
	$LQ_{\oplus}^{-}$	0.87	0.58	$\{VL/0.75, L/0.25, H/0.5, VH/0.5\}$	$\{VL/0.95, L/0.25, H/0.5, VH/0.5\}$

Table 2. Intermediate and final results of the evaluation.

precise single value, as proposed in [3], Model IV now proposes a possibility distribution over the values that can be expected for environmental receptors.

These models introduce a more qualitative approach than [3] and show that fuzzy logic provides a tool for SEA that is more appealing for the domain experts.

In this work we implemented the simple one-way relation included into the co-axial matrices already used in the Emilia-Romagna region. However, environmental systems are very complex, and seldom relations are only in one direction, but environmental receptors could have an effect on the impacts or raise the need to perform some compensation activity in the future regional plans. In future work, we plan to study such effects.

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