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Sewer rehabilitation criteria evaluated by fusion of fuzzy indicators

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Abstract This paper deals with definition and assessment of decision criteria for sewer asset management. The work was prepared within a doctoral thesis (Ibrahim, 2008) and is part of a research program (INDIGAU, 2007-2010, www.indigau.fr) supported by the French National Research Agency (ANR). Three main ideas are exposed and illustrated in this paper. 1) Each rehabilitation criterion may be seen as the result of successive aggregations of complementary indicators provided by various methods or sources (visual inspection, O&M data, investigation techniques, etc.) at several spatial scales (sewer segment, catchment). 2) Combining indicators may be computed by means of a limited number of “if ... then ...” rules. The French RERAU¹ method provides 4x4 tables defining how to combine couples of indicators, each one being evaluated on a four-grade ordinal scale (G4 being the highest gravity). 3) The aggregation tables can be converted into fuzzy aggregation rules associated to the use of fuzzy indicators. Compared to crisp data and rules, the use of fuzzy indicators and fuzzy rules provides finer results and improves the robustness of the fusion process.

Introduction: the need to link the condition of assets to the quality of service

Baptista & Alegre (2007) have pointed out that a major part of strategic asset management (SAM) is the “capability of assessing the infrastructure performance at both asset-specific and system levels”, “taking into account the utility objectives, on the one hand, and all the other components of the utility management, on the other hand.” D. Parsons (2006), from OFWAT, underlines that “it is essential to link asset behaviour (and failure modes) to service delivered”. One basis of asset management should be the understanding of the link between the condition of the physical assets and the quality of service provided to customers.

This need was addressed within the French R&D RERAU program, involving research teams, consulting companies and French utilities such as the Urban Communities of Lille, Lyon, Strasbourg, Caen, etc. The proposed methodology is detailed in a guidebook (Le Gauffre *et al.*, 2004, in French)

¹ RERAU: « Réhabilitation des Réseaux d’Assainissement Urbains » (*rehabilitation of urban sewer networks*).

and is presented in (Le Gauffre *et al.*, 2007). This contribution to sewer asset management may be summarized as follows:

- two sets of similar criteria are defined for supporting the definition of investigation programs and rehabilitation programs;
- investigation and rehabilitation criteria may be calculated from complementary performance indicators (PIs) relating to defects, dysfunctions or impacts;
- PIs may be assessed by observation (by means of visual inspection, investigation techniques, monitoring, etc.), by estimation (ageing models, etc.), or by combination of other PIs;
- PIs refer to individual assets or to subsystems;
- each PI is assessed on a four-grades scale and relationships between PIs are modelled by qualitative models (4x4 tables);
- each proposed criterion assesses a contribution of a particular dysfunction of a sewer segment to a particular impact. Each of the eight defined impacts is linked to some of the ten source dysfunctions (Figure 1).

Dysfunctions: INF: infiltration, EXF: exfiltration, HYD: decrease in hydraulic capacity, SAN: sand silting, BLO: blockage, SPD: destabilization of the ground-pipe system, COR: degradation due to corrosion, ROO: degradation due to roots intrusion, ABR: degradation from abrasion, COL: risk of collapse.

		DYSFUNCTIONS									
		INF	EXF	HYD	SAN	BLO	SPD	COR	ROO	ABR	COL
IMPACTS	POL	X		X	X	X					
	POG		X	X	X	X					
	NUH			X	X	X					
	TRA				X	X					X
	DAB		X								X
	OCS	X			X	X					
	OCP	X									
	SLC						X	X	X	X	

Impacts: POL: pollution of surface waters, POG: pollution of ground and groundwater, NUH: nuisances of a hydraulic nature (flooding, etc.), TRA: disruption of surface activities (traffic, etc.), DAB: damages to the built environment, OCS: network operation surplus costs, OCP: treatment plant operating surplus costs, SLC: cost associated to shortened lifetime.

Figure 1. Decision criteria defined by linking impacts and source dysfunctions.

R/POL/BLO, R/OCP/INF, R/TRA/COL and R/SLC/SPD are four examples of criteria that may be used to define rehabilitation needs and priorities:

- R/POL/BLO: sewer segment contributing to pollution of surface water (POL) due to spillages induced by repeated blockages (BLO);
- R/OCP/INF: sewer segment contributing to infiltration (INF) inducing treatment plant operation surplus costs (OCP);
- R/TRA/COL: risk of traffic disruption (TRA) due to collapse (COL);
- R/SLC/SPD: shortened lifetime cost (SLC) due to destabilization of the ground-pipe system (SPD).

Another example is detailed in next section.

Linking the asset condition to impacts

1) Each criterion results from the aggregation of complementary indicators

Each rehabilitation criterion may be seen as the result of successive aggregations of complementary indicators provided by various methods or sources (visual inspection, O&M data, investigation techniques, etc.) at several spatial scales (sewer segment, catchment). Figure 2 exposes a criterion defined in the RERAU method (Le Gauffre *et al.*, 2004, 2007).

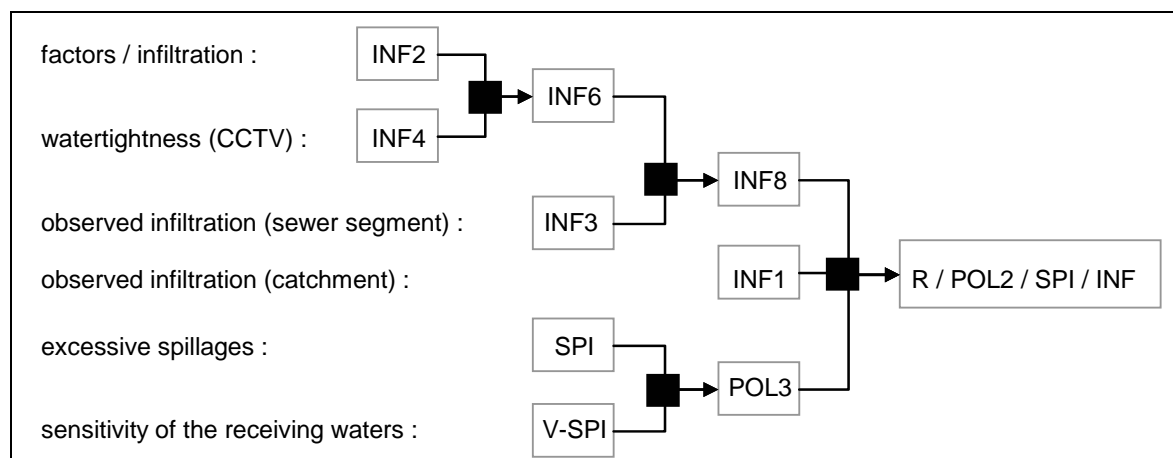


Figure 2. Indicators related to criterion R/POL2/SPI/INF “Infiltration contributing to Pollution due to dry-weather spillages”

INF2 is an indicator relating to the factors influencing water infiltration into the sewer segment: water table always or periodically above pipe, and type of backfill (watertight or permeable).

INF4 is derived from visual inspection results (Cherqui *et al.*, 2008, 2009; Ibrahim, 2008) and is a measure of watertightness deficiency.

INF6 is the result of aggregating INF2 and INF4: it is an indirect measure of a dysfunction (infiltration).

INF3 is a direct measure of dysfunction infiltration that may be available (for instance if infiltration has been observed during the inspection) or not (if no infiltration has been observed in a non favourable context such as a dry period).

INF8 refers to the conclusion that may be obtained – at the sewer segment scale – by fusion of two indicators (INF6 and INF3) derived from complementary sources.

Finally, criterion R/POL2/SPI/INF links indicator INF8 with one type of possible impacts: *Infiltration* contributing to *Pollution* due to dry-weather *Spillages* (or separate sanitary sewers overflows). If abnormal spillages (SPI) are affecting sensitive receiving waters (POL3), and if a high rate of infiltration water (INF1) is an explanation of these spillages (Raynaud *et al.*, 2008), sewer segments that contribute to infiltration (INF8) should be listed as rehabilitation needs.

2) Fusion of indicators with “if ... then ...” rules

Base data are expressed with many different units. For the purpose of combining these data by means of a limited number of “if ... then ...” rules, a common framework is defined and used for converting data into indicators. This framework combines two principles:

- each indicator is assigned a grade out of four possible grades, between G1 (no or low deficiency) and G4 (worst situation);
- indicators are combined by means of aggregation tables.

The RERAU guidebook (Le Gauffre *et al.* 2004) provides 4x4 tables defining how to combine couples of indicators (black boxes in Figure 2).

Grabisch *et al.* (1998) or Bloch & Hunter (2001) discuss the issue of aggregating complementary information or assessments. Possible aggregation operators may be classified into several categories: conjunctive, disjunctive, compensative, non-compensative. Aggregation tables used in the RERAU PI processing system refer to these categories:

- conjunctive: two indicators relate to two required conditions for an event or a situation (e.g. a sewer segment is said to contribute to a dysfunction if this dysfunction is observed and if the sewer segment is in a poor condition, regarding this dysfunction); the min operator is commonly used as conjunctive operator;
- disjunctive: two indicators relate to two alternative ways of getting an event (cause1 or cause2); the max operator is commonly used as disjunctive operator;
- compensative: refers to a situation where two indicators are combined for assessing a resulting effect (e.g. an impact indicator is evaluated by combining a dysfunction indicator with a vulnerability indicator), the arithmetic mean is a relevant operator for this reasoning ;
- non-compensative: a first case of non compensation is a situation where two indicators refer to two phenomena that may be reinforced by synergy; taking into account this interaction requires a specific synergy operator; a second case of non compensation is a situation where two indicators refer to two parallel sources for assessing a state or a phenomenon: reliability of assessment is reinforced when both sources agree; on the contrary if sources provide different conclusions a

composite indicator will retain “all answers from all sources at the price of increased imprecision” (Bloch and Hunter, 2001).

Figure 3 provides some examples of (crisp) aggregation tables:

- PI1 and PI2 are two indicators combined with a “mean” operator;
- the result (PI3) and PI4 are combined with a “max” operator;
- finally criterion C is evaluated by combining PI5 and PI6 with a “min” operator.

Each cell of a table defines one single rule, for instance: “if PI1 = G2 and PI2 = G4, then PI3 = G3”.

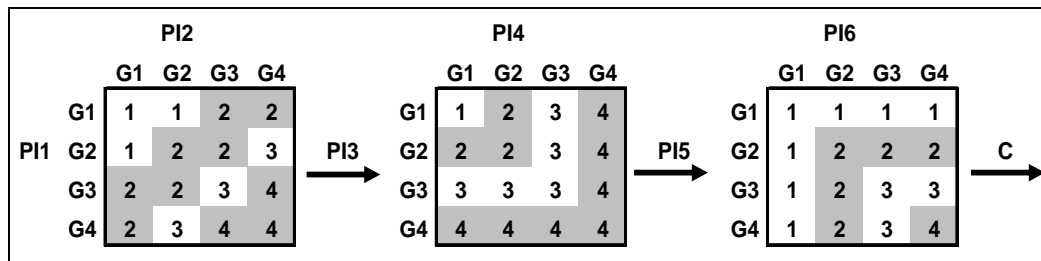


Figure 3. Three examples of aggregation tables (“1” stands for “G1”, “2” for “G2”, etc.)

3) Fusion of fuzzy indicators by using fuzzy rules

The RERAU framework allows combining various types of base data, but induces two issues, the first one regarding the conversion of quantitative data into a grade, the second one regarding the aggregation of two grades.

Converting a quantitative base data into a grade may be done by means of four thresholds (or cut-off values). For instance, if we denote S_1 the cut-off value between grades G1 and G2 and x a base data, then a crisp conversion means that $(x \leq S_1)$ implies that the indicator is assigned grade G1, while $(x > S_1)$ implies that the indicator is assigned grade G2 at least; thus $(x = S_1 - \varepsilon)$ and $(x = S_1 + \varepsilon)$ lead to two different assignments. This common problem may be addressed by using a fuzzy representation: within this approach a given value x may lead to assign grade G1 and grade G2 with two corresponding weights or membership values (e.g. 0.6 and 0.4).

Combining two indicators for assessing a high level indicator (or a criterion) may pose some problems: for instance, averaging grade G2 (assessment of indicator X) and grade G3 (assessment of indicator Y) may lead to two possible crisp aggregation results: G2 or G3; a pessimistic view will give G3, while an optimistic view will give G2. This question may be addressed by using a fuzzy arithmetic mean operator. Averaging G2 and G3 could lead to the following result: indicator Z (derived from X and Y) is assigned a grade which is “between G2 and G3” or “half G2 – half G3”; we will denote “0, 0.5, 0.5, 0” this aggregation result ($\mu(G1) = 0, \mu(G2) = 0.5, \mu(G3) = 0.5, \mu(G4) = 0$.)

A third issue leads to prefer fuzzy operators to crisp operators. The case where two different sources provide different conclusions (in evaluating the same assumption) is a good example of a need for

propagating uncertainty within the PI system: “at the combination level, the choice of an operator is crucial. Conjunctive combination operators are discontinuous in the presence of conflicts and may provide no interesting results at all. Averaging is not realistic since such operators may provide answers that are given by none of the sources, or even rejected individually by each source. If some of the sources are assumed to be reliable, disjunctive operators can be used, which will retain all answers from all sources at the price of increased imprecision” (Bloch and Hunter, 2001).

The next section is dedicated to the implementation of a fuzzy rule-based information fusion system.

Implementing a fuzzy rule-based information fusion system

Five steps and issues are presented in this section, following Mauris *et al.* (1996):

- representing an indicator with fuzzy linguistic variables;
- representing each aggregation table with “if... then...” rules;
- combining two premises of a rule;
- fuzzy representation of the implication;
- aggregating the results of several rules.

1) Representing an indicator with fuzzy linguistic variables

The four terms G1, G2, G3 and G4 may be viewed as four fuzzy subsets allowing a numeric/symbolic conversion. The fuzzy subset theory led to the development of the concept of fuzzy meanings and fuzzy description (Mauris *et al.* 1996):

- fuzzy meanings are the representation of fuzzy subsets corresponding to linguistic terms: $\mu_{L_i}(x)$ denotes the membership function associated to the linguistic term L_i (Figure 4);
- the fuzzy description is a simple way of describing a measurement with words: $\mu_x(L_i)$ denotes the membership value associated to the linguistic term L_i , for a given numeric value (e.g. $x = 12$ in Figure 4).

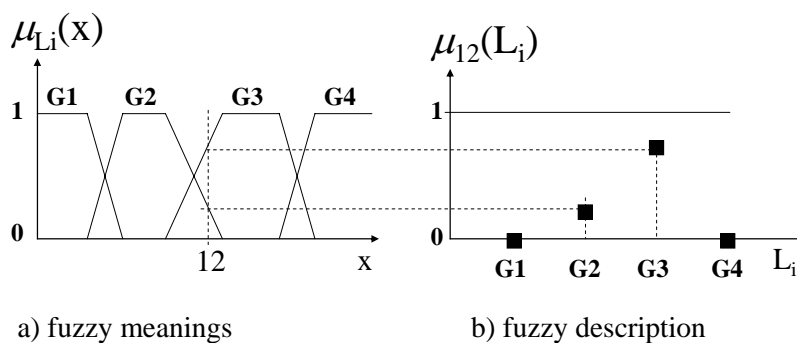


Figure 4. Link between fuzzy meanings and fuzzy description

2) Representing each aggregation table with “if... then...” rules

Each aggregation table can be expressed as a set of if/then rules. We denote:

- $R_{i,j,k}$ the rule: “if X is G_i and Y is G_j then Z is G_k ”, with $G_i, G_j, G_k \in \{G1, G2, G3, G4\}$
- $\mu_\Gamma(i, j, k)$ the degree of validity (or weight) of the rule $R_{i,j,k}$ for operator Γ , an aggregation table defined for a given indicator;

Figure 5 provides an example of an aggregation table with crisp and fuzzy conclusions:

- case [“ X is $G1$ ” and “ Y is $G1$ ”] gives a crisp conclusion: “ Z is $G1$ ” ($\mu_\Gamma(1,1,1)=1$, and $\mu_\Gamma(1,1,k)=0$ for $k=2,3,4$);
- case [“ X is $G2$ ” and “ Y is $G3$ ”] gives a fuzzy conclusion: $\mu_\Gamma(2,3,k)=0.5$ for $k=2$ & 3 and $\mu_\Gamma(2,3,k)=0$ for $k=1$ & 4 .

Y X	G1	G2	G3	G4
G1	1.0 ; 0.0 ; 0.0 ; 0.0	0.5 ; 0.5 ; 0.0 ; 0.0	0.0 ; 1.0 ; 0.0 ; 0.0	0.0 ; 0.5 ; 0.5 ; 0.0
G2	0.5 ; 0.5 ; 0.0 ; 0.0	0.0 ; 1.0 ; 0.0 ; 0.0	0.0 ; 0.5 ; 0.5 ; 0.0	0.0 ; 0.0 ; 1.0 ; 0.0
G3	0.0 ; 1.0 ; 0.0 ; 0.0	0.0 ; 0.5 ; 0.5 ; 0.0	0.0 ; 0.0 ; 1.0 ; 0.0	0.0 ; 0.0 ; 0.5 ; 0.5
G4	0.0 ; 0.5 ; 0.5 ; 0.0	0.0 ; 0.0 ; 1.0 ; 0.0	0.0 ; 0.0 ; 0.5 ; 0.5	0.0 ; 0.0 ; 0.0 ; 1.0

Figure 5. An aggregation table with fuzzy conclusions: four values $\mu_\Gamma(i, j, k)$; $k=1,2,3,4$ are defined for each cell of the table.

3) Combining two premises of a rule

Each aggregation table uses two indicators for defining a high level indicator. Each associated rule has two premises connected by an “and” operator (X is L_i and Y is L_j).

We denote $\mu(L_i, L_j)$ the membership value associated to the pair (L_i, L_j) . If we make the assumption that the two indicators are independent, $\mu(L_i, L_j)$ is decomposable (Mauris *et al.* 1996) and can be derived from $\mu_x(L_i)$ and $\mu_y(L_j)$ by using an operator of intersection, denoted O_1 (1).

$$\mu(L_i, L_j) = \mu_x(L_i) O_1 \mu_y(L_j) \tag{1}$$

Several operators of intersection may be used: *min*, *product*, etc. Results presented in this paper have been computed with a *product* operator:

$$\mu(L_i, L_j) = \mu_x(L_i) \times \mu_y(L_j) \tag{2}$$

4) Fuzzy implication

We denote $\mu(L_i, L_j, L_k)$ the membership value associated to "Z is L_k " which is inferred from "X is L_i " and "Y is L_j " by using the rule $R_{i,j,k}$.

This value $\mu(L_i, L_j, L_k)$ can be derived from $\mu(L_i, L_j)$ and from $\mu_\Gamma(i, j, k)$, degree of validity of the rule $R_{i,j,k}$ for the aggregation table Γ , by means of an intersection operator, denoted O_2 (e.g. *min* operator or *product* operator) (Mauris *et al*, 1996):

$$\mu(L_i, L_j, L_k) = \mu(L_i, L_j) O_2 \mu_\Gamma(i, j, k) \quad (3)$$

Using (1) for $\mu(L_i, L_j)$, we obtain:

$$\mu(L_i, L_j, L_k) = (\mu(L_i) O_1 \mu(L_j)) O_2 \mu_\Gamma(i, j, k) \quad (4)$$

Results presented in this paper have been computed with a *product* operator:

$$\mu(L_i, L_j, L_k) = \mu(L_i) \times \mu(L_j) \times \mu_\Gamma(i, j, k) \quad (5)$$

5) Aggregating the results of several rules

Conclusion "Z is L_k ", concerning a high level indicator, may be inferred from several rules $R_{i,j,k}$. We denote $\mu(L_k)$ the membership value associated to the linguistic term L_k . This value is calculated by considering all the rules inferring this conclusion, by means of a union operator denoted O_3 :

$$\mu(L_k) = O_3_{i=1\dots 4, j=1\dots 4} \mu(L_i, L_j, L_k) \quad (6)$$

Results presented in this paper have been computed with a *sum* operator:

$$\mu(L_k) = \sum_{i=1\dots 4, j=1\dots 4} \mu(L_i, L_j, L_k) \quad (7)$$

Benefits of using a fuzzy rule-based information fusion system

Numerical experiments have been performed in order to assess the benefits of using a fuzzy rule-based information fusion system instead of crisp indicators and criteria. We expose two demonstrative examples:

- example 1 shows that the use of fuzzy indicators and fuzzy aggregation rules provides finer results than crisp indicators;
- example 2 is used to show that fuzzy tools improve the robustness of the fusion process.

Example 1: comparing two sewer segments

This first example is using crisp and fuzzy rules that are presented in Figure 6, regarding criterion R/POL2/SPI/INF “Infiltration contributing to Pollution due to dry-weather spillages” (this criterion and relative indicators were presented in Figure 2).

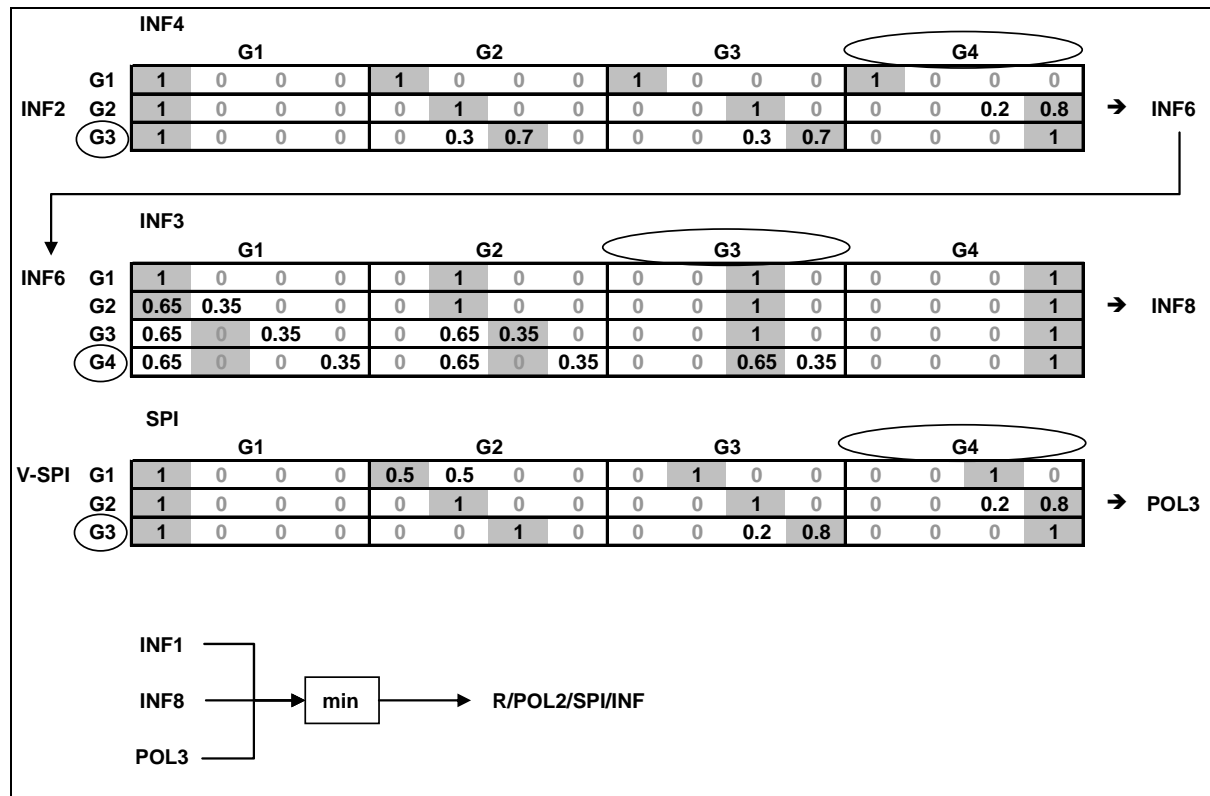


Figure 6. Fuzzy rules used for assessing criterion R/POL2/SPI/INF, with corresponding crisp rules represented by shaded cells, and values of indicators (in circles) for sewer segment SS1.

We compare two sewer segments (SS1 and SS2) according to criterion R/POL2/SPI/INF. Grades assigned to base indicators and grades assigned to the criterion are given in Table 1.

For SS1, combining “INF2 is G3” and “INF4 is G4” gives “INF6 is G4” (with crisp and fuzzy rules): major watertightness deficiency combined to water table above pipe leads to a high level of presumption regarding water infiltration into SS1.

Additionally, direct observation provides “INF3 is G3”. INF3 and INF6 are two possible ways or sources for assessing water infiltration into pipe segment SS1. In this case these two indicators provide similar results, without conflicts. Crisp aggregation gives “INF8 is G3” whereas fuzzy aggregation gives $\mu(G3) = 0.65$, $\mu(G4) = 0.35$. The same values ($\mu(G3) = 0.65$, $\mu(G4) = 0.35$) are obtained for criterion R/POL2/SPI/INF (as INF1, V-SPI and SPI have been assigned the highest grades, Table 1).

For sewer segment SS2, crisp aggregation and fuzzy aggregation give “INF8 is G3.” Indicator SPI is assigned grade G2 (few events registered during 3-5 years). Receiving waters are considered as sensitive (G2) to very sensitive (G3): $\mu(G2) = 0.50$, $\mu(G3) = 0.50$, whereas a crisp assessment leads to assign grade G3 to indicator V-SPI.

The final result for SS2 is “R/POL2 is G3” within a crisp assessment procedure; whereas a fuzzy assessment process gives $\mu(G2) = 0.50$, $\mu(G3) = 0.50$.

Table 1. Base indicators and criterion R/POL2/SPI/INF evaluated for two sewer segments

Base indicators & criterion R/POL2	Sewer segments			
	Sewer segment SS1		Sewer segment SS2	
INF2 (infiltration factors)	G3		G2	
INF4 (watertightness deficiency)	G4		G3	
INF3 (observed infiltration, segment scale)	G3		G3	
INF1 (observed infiltration, catchment scale)	G4		G4	
V-SPI (sensitivity of receiving waters)	G3		G3	
SPI (abnormal spillages)	G4		G2	
Crisp assessment of R/POL2/SPI/INF	G3		G3	
Fuzzy assessment of R/POL2/SPI/INF	$\frac{0.00}{G1}$	$\frac{0.00}{G2}$	$\frac{0.65}{G3}$	$\frac{0.35}{G4}$
	$\frac{0.00}{G1}$	$\frac{0.50}{G2}$	$\frac{0.50}{G3}$	$\frac{0.00}{G4}$

This example shows that a fuzzy assessment process provides finer results than those provided by crisp indicators and crisp rules. These two sewer segments are assigned the same grade (G3) with a crisp method, but can be clearly distinguished with a fuzzy assessment method: SS1 appears as a priority projects whereas the condition of SS2 appears less severe.

Example 2: improving robustness of the performance assessment

Figure 7 illustrates a situation where visual inspection may lead to two different condition assessments: let us denote x_1 (respectively x_2) the value of a numerical score x (Le Gauffre *et al.*, 2007) obtained by interpretation of the defects reported by operator 1 (respectively operator 2). Dirksen *et al.* (2007) have shown that results obtained from 2 different human operators may be highly different.

A crisp assessment of indicator INF4 can be obtained by comparing x_1 or x_2 with cut-off values. Here we consider the two following scenarios:

- scenario 1: $x = x_1$ is close to the cut-off value S_2 between grades G2 and G3, and $x_1 < S_2$; this leads to the crisp conclusion “INF4 is G2”;

- scenario 2: $x = x_2$ is close to the cut-off value S_2 , and $x_2 > S_2$; this leads to the crisp conclusion “INF4 is G3”;

Within a fuzzy assessment process the two scenarios are:

- scenario 1: value x_1 leads to the fuzzy conclusion $\mu(G2) = 0.60, \mu(G3) = 0.40$;
- scenario 2: value x_2 leads to the fuzzy conclusion $\mu(G2) = 0.40, \mu(G3) = 0.60$.

Within this fuzzy approach, different but similar data ($x_2 \cong x_1$) will provide similar conclusions.

The same applies when considering uncertainty linked to the definition of a crisp cut-off value.

Defining a crisp cut-off value is a calibration process (Ibrahim *et al.* 2007; Cherqui *et al.* 2009) that is using available data (more or less reliable) together with parameters and hypotheses that are more or less precise (importance given to assignment errors such as a false negative or a false positive, etc.)

For instance, S'_2 may be an alternative value to S_2 . Figure 7 displays a situation where $S_2 < x_2 < S'_2$, which means that – with a given condition assessment (quantified by x_2) – a crisp conclusion may switch from G3 to G2 if the cut-off value slightly varies from S_2 to S'_2 .

Using a fuzzy framework provides a more robust assessment: $\mu(G2)$ and $\mu(G3)$ will slightly vary with small variations of the parameters and hypotheses that are used in the calibration process (Cherqui *et al.* 2009).

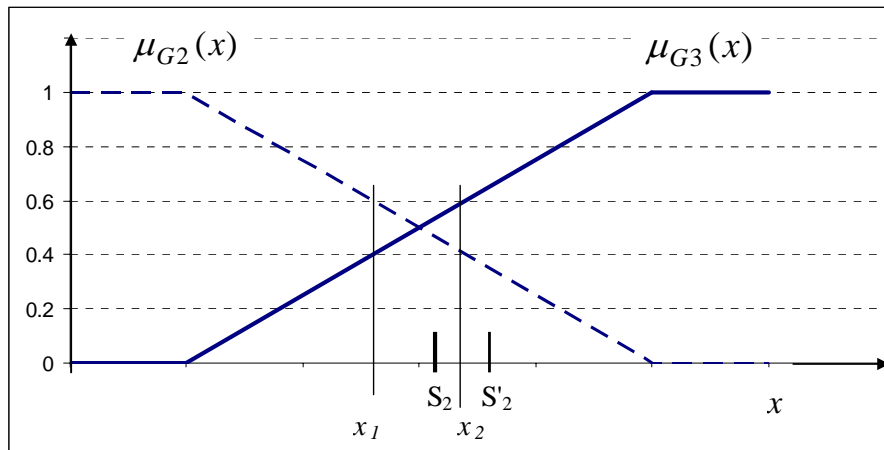


Figure 7. Two possible values x_1 & x_2 of a score x computed after visual inspection of a sewer segment, are translated into grades by comparison to a crisp cut-off value (S_2 or S'_2) or by using fuzzy sets.

Combining INF4 with other indicators leads to the results presented in Table 2. The first two steps of the aggregation process are shown in Figure 8.

Within scenario 2, for INF4, value x_2 leads to the fuzzy conclusion $\mu(G2) = 0.40, \mu(G3) = 0.60$.

For INF2, $\mu(G2) = 1$. Combining INF4 and INF2 provides $\mu(G2) = 0.40, \mu(G3) = 0.60$ for INF6.

For INF3, $\mu(G2) = 1$. INF6 and INF3 are combined by using 3 rules :

- “INF3 is G2” and “INF6 is G2” leads to INF8 is G2” with $\mu_{INF6}(2,2,2) = 1$;
- “INF3 is G2” and “INF6 is G3” leads to INF8 is G2” with $\mu_{INF6}(2,3,2) = 0.65$;
- “INF3 is G2” and “INF6 is G3” leads to INF8 is G3” with $\mu_{INF6}(2,3,3) = 0.35$;

Aggregating results of these 3 rules provides the assessment of INF8 : $\mu(G2) = 0.79, \mu(G3) = 0.21$
 $(\mu(G2) = (0.4 \times 1 \times 1) + (0.6 \times 1 \times 0.65), \mu(G3) = (0.4 \times 1 \times 0) + (0.6 \times 1 \times 0.35))$.

Finally, a similar result is obtained for criterion R/POL2/SPI/INF after combining INF8 with other indicators (INF1, V-SPI, SPI).

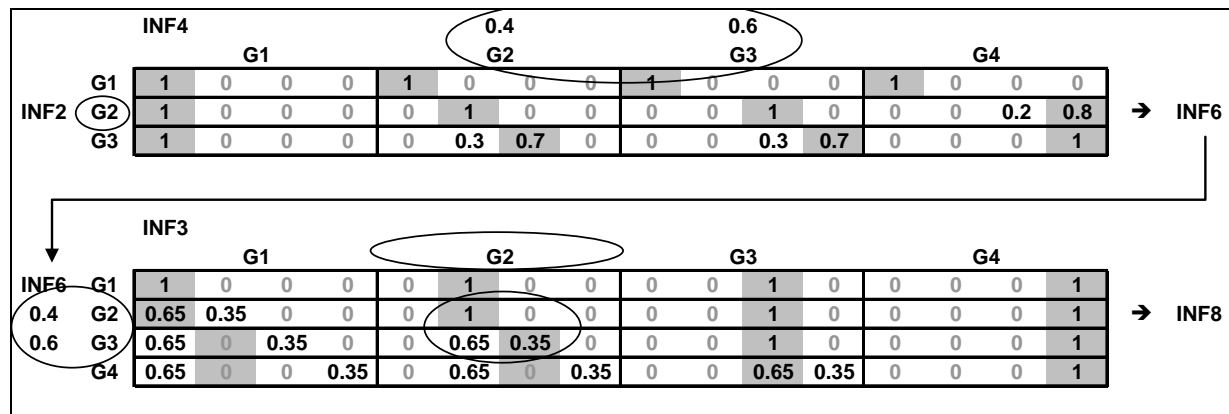


Figure 8. Fuzzy assessment of indicator INF8 within scenario 2

Table 2. Comparison of crisp and fuzzy assessments of a sewer segment within scenarios 1 and 2.

	indicator INF4	criterion R/POL2/SPI/INF
Scenario + assessment method		
Scenario 1 + crisp assessment	G2	G2
Scenario 2 + crisp assessment	G3	G3
Scenario 1 + fuzzy assessment	$\frac{0.00}{G1}, \frac{0.60}{G2}, \frac{0.40}{G3}, \frac{0.00}{G4}$	$\frac{0.00}{G1}, \frac{0.86}{G2}, \frac{0.14}{G3}, \frac{0.00}{G4}$
Scenario 2 + fuzzy assessment	$\frac{0.00}{G1}, \frac{0.40}{G2}, \frac{0.60}{G3}, \frac{0.00}{G4}$	$\frac{0.00}{G1}, \frac{0.79}{G2}, \frac{0.21}{G3}, \frac{0.00}{G4}$

Results in Table 2 show that a crisp assessment framework leads to switch from grade G2 to grade G3 (or the opposite) for criterion R/POL2/SPI/INF when a slight change occurs in reporting defects or in calibrating a crisp cut-off value for indicator INF4.

On the contrary, a fuzzy framework allows dealing with uncertainties linked to data and to rules. This leads to smooth the assessment process and provides more robust results.

As robustness is a major criterion for disseminating models and tools towards utilities and consulting companies, this example illustrates, together with other works such as (Bagheri *et al.* 2006; Rajani *et al.* 2006; Sadiq *et al.* 2004), the benefits of designing performance indices and decision support tools based on a fuzzy inference approach.

Summary and conclusion

One basis of asset management should be the understanding of the link between the condition of the physical assets and the quality of service provided to customers. Within this concern, three main ideas are exposed and illustrated in this paper:

- a rehabilitation criterion may be seen as the result of successive aggregations of complementary indicators provided by various methods or sources (visual inspection, O&M data, investigation techniques, etc.) at several spatial scales (sewer segment, catchment);
- combining indicators may be computed by means of a limited number of “if .. then ...” rules; the French RERAU method provides 4x4 tables defining how to combine couples of indicators, each one being evaluated on a four-grade ordinal scale (G4 being the highest gravity);
- to deal with uncertainty linked to base data and to knowledge or decision rules, the crisp aggregation tables can be converted into fuzzy aggregation rules associated to the use of fuzzy indicators.

Fuzzy indicators allow dealing with the uncertainty linked to base data (for instance a score calculated after visual inspection, based on reported defects) or linked to PI calibration processes (for instance the uncertainty linked to the hypotheses that are used for defining a cut-off value).

Fuzzy rules allow dealing with imprecise human reasoning when combining complementary indicators into a more synthetic indicator. Additionally, fuzzy rules (rules with several conclusions) allow to compute the uncertainty arising from the use of two complementary sources of information on a given phenomenon (for instance INF3 and INF6 may reinforce themselves if they provide same results, this will lead to a low level of fuzziness for composite indicator INF8; on the contrary two different results will lead to a high level of fuzziness for INF8).

Examples provided in this paper tend to demonstrate that using a fuzzy framework, instead of crisp indicators and crisp rules, improves the assessment process by providing finer and more robust conclusions:

- example 1 shows that the use of fuzzy indicators and fuzzy aggregation rules provides finer results than crisp indicators;
- example 2 is used to show that fuzzy tools improve the robustness of the fusion process.

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