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Sewer asset management: fusion of performance indicators into decision criteria

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ABSTRACT

Within the RERAU methodology, each rehabilitation criterion is assigned a grade out of 4 possible ones. This grade results from successive aggregations of performance indicators. Issues related to base data (uncertain or imprecise data) and to fusion (conflicting or reinforcing indicators) lead to envisage a fuzzy method for processing the proposed set of performance indicators. Five issues are discussed in this paper: 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 INTRODUCTION

1.1 The RERAU methodology

A French R&D program (RERAU, 1999-2004) was dedicated to the definition of a set of criteria for prioritising investigation and rehabilitation measures for sewer segments. Each criterion was defined as a combination of complementary performance indicators (Le Gauffre *et al.*, 2004). These performance indicators use information that is obtained from complementary sources: visual inspections of sewer segments, network monitoring, data issued from network and treatment plant operation, data related to the vulnerability of the build environment and of the receiving waters.

The process that was used for defining indicators and decision criteria is explained in (Le Gauffre *et al.*, 2007) with 3 main steps: 1) Setting up typologies for defects, dysfunctions and impacts; 2) Deriving indicators for defects, dysfunctions and impacts; 3) Combining dysfunction indicators and impact indicators into decision criteria.

Two types of dysfunctions are distinguished. Infiltration (INF), exfiltration (EXF), sand silting (SAN), blockage (BLO), destabilization of ground-pipe system (SPD), etc. are source dysfunctions occurring at the pipe scale. Flooding (FLO) and excessive spillage (CSO) occur on some specific sewer segments, but indeed refer to primary dysfunctions (like silting or blockage) which may be located some distance downstream, or in some cases upstream.

Each proposed criterion assesses a contribution of a particular dysfunction of a sewer segment to a particular impact. Each of the 8 defined impacts is linked to some of the 10 source dysfunctions (Figure 1). 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 due to spillages induced by repeated blockages;

- R/OCP/INF: sewer segment contributing to infiltration inducing treatment plant operation surplus costs;
- R/TRA/COL: risk of traffic disruption due to collapse;
- R/SLC/SPD: shortened lifetime cost due to destabilization of the ground-pipe system.

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
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: networks 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

1.2 The INDIGAU research program

A new R&D program (INDIGAU, 2007-2010) is dedicated to calibration and experiments of models that were defined within the RERAU program.

Another goal of the INDIGAU program is to address issues linked to the characteristics of available data and knowledge: uncertain, imprecise and incomplete data. This research task refers to the aggregation or “fusion” of complementary data provided by several sources. In the case of sewer asset management, the various sources are results of visual inspection, on-site measurements, hydraulic modelling, registered failures, etc.

Within the RERAU methodology each criterion is assigned a grade out of 4 possible ones (from G1 - good condition ... to G4 - very bad condition). This

grade results from successive aggregations of indicators. Figure 2 provides three examples of 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.

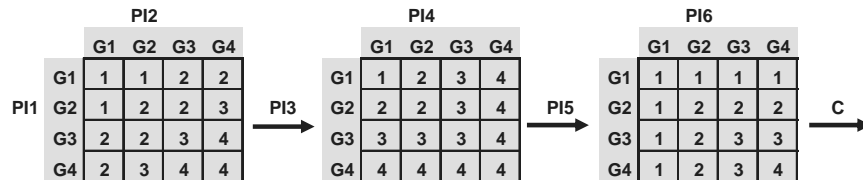


Figure 2. EACH CRITERION RESULTS FROM SUCCESSIVE AGGREGATION OPERATIONS

2. ISSUES INDUCED BY BASE DATA

2.1 A typology of base performance indicators

We define several types of base performance indicators together with the associated sources of uncertainty.

Type A: indicators directly derived from inspection results; for instance infiltration may be observed during a visual inspection; for these PIs sources of uncertainty are: non registered dysfunction, wrong code, etc.

Type B: indicators derived from a synthesis of the results of a visual inspection; for instance “watertightness deficiency” (risk of infiltration) can be assessed by considering the number and the seriousness of observed defects; for these PIs sources of uncertainty are: non registered defects, wrong codes, cut-off values, etc. (see 2.2).

Type C: indicators directly derived from O&M data, i.e. registered events (blockages) or actions (cleansing operations); sources of uncertainty are: non registered events, cut-off values, etc.

Type D: indicators derived from O&M data (flooding or spillage events) associated with a hydraulic calculation procedure for defining sewer segments that may have caused these events; for these PIs sources of uncertainty are: non registered events, cut-off values, hydraulic calculation procedure, etc.

Type E: indicators derived from monitoring data (for instance infiltration flows); sources of uncertainty are: uncertainty on measurements, cut-off values, etc.

Type F: indicators related to external factors of defects and dysfunctions (type of soil, water table level, etc.); sources of uncertainty are: poor knowledge of the environment, etc.

Type G: indicators representing urban vulnerabilities (possible consequences of dysfunctions); sources of uncertainty are: poor knowledge of the urban environment of the network, etc.

Type H: indicators derived from O&M data for assessing consequences on O&M costs; sources of uncertainty are: available cost data.

2.2. PIs derived from a synthesis of the results of visual inspections

Results of a visual inspection of a particular segment, regarding a given dysfunction (let say: infiltration), can be synthesised by calculating a score S aggregating single scores associated to observed defects (cracks, missing wall, etc.). Translating this score S into a grade out of 4 possible ones (G1, G2, G3 or G4) requires to compare score S with 3 cut-off thresholds. This procedure leads to 3 problems. Problems 1 & 2 refer to the calibration process while problem 3 relates to the use of the cut-off thresholds.

Problem 1. Score S is not an exact expression of the expertise: if we compare scores with expert assessment of a sample of sewer segments we can see that it is not possible to deduct the condition grade from the score without any errors (Figure 3).

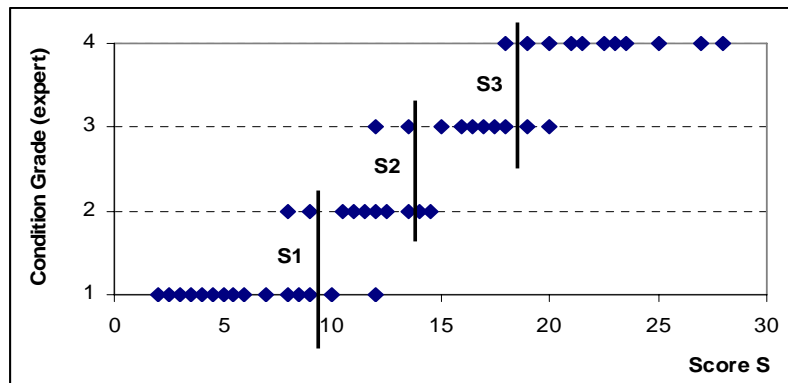


Figure 3. CUT-OFF THRESHOLDS (S1, S2, S3) ARE USED TO ASSIGN A GRADE AFTER CALCULATION OF A SCORE S.

Problem 2. The chosen cut-off thresholds do not rely on objective knowledge but will be derived from a calibration procedure using expert judgments as references (Ibrahim *et al.* 2007). However, for a given segment, the judgments expressed by several experts may be very different from each others (Werey *et al.* 2008). That poses a problem for defining a crisp reference.

Problem 3. A score that is close to a cut-off threshold may underestimate the right score (for instance if some defects have not been registered, Dirksen *et al.* 2007) or it may overestimate the right score (for instance if a code has been used instead of the right one). These errors may lead to two types of misclassification: the grade is underestimated (e.g. G3 instead of G4) or overestimated (G4 instead of G3).

In (Ibrahim *et al.* 2007) we proposed a calibration criterion for fixing cut-off thresholds: *MC misclassification cost* integrates simultaneously underestimation and overestimation errors. Thus imprecision of assessment is taken into account: the thresholds are chosen in order to be the most cost-efficient. However, this procedure has a meaning exclusively at the scale of the asset stock; it induces punctual errors (at the scale of some sewer segments) that may be important. Fuzzy sets theory provides a way of addressing these issues. Grades G1, G2, G3 and G4 may be seen as four fuzzy sets. With this approach a sewer segment will be assigned a fuzzy description, for instance: 0.7 for grade G3 and 0.3 for grade G4, on a given indicator (see 3.2.2.)

3. FUSION OF PERFORMANCE INDICATORS

3.1. Fuzzy rules for assessing rehabilitation criteria

Issues related to base data (2.1) and to fusion (see 3.2) lead to envisage a fuzzy method for processing the proposed set of performance indicators. Five issues are discussed in this section (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.

3.1.1. 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).

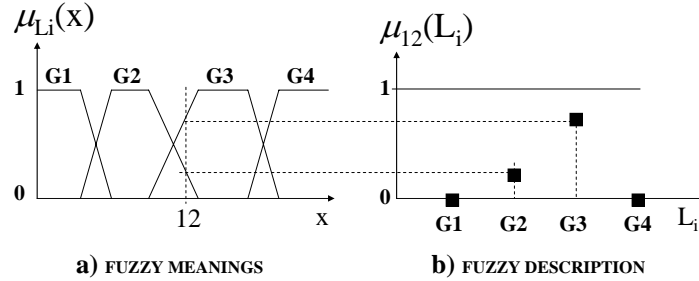


Figure 4. LINK BETWEEN FUZZY MEANINGS AND FUZZY DESCRIPTION

3.1.2. Representing each aggregation 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 L_i and Y is L_j then Z is L_k ”,
with $L_i, L_j, L_k \in \{G1, G2, G3, G4\}$.
- $\mu_{\Gamma}(i, j, k)$ the degree of validity (or weight) of the rule $R_{i,j,k}$ for operator Γ (for instance: min, max, mean, etc.)

	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. EXAMPLE OF AN AGGREGATION TABLE WITH FUZZY CONCLUSIONS
 (EACH CELL PROVIDES 4 VALUES: $\mu_{\Gamma}(i, j, k)$ FOR $k = 1 \dots 4$)

3.1.3. Combining two premises of a rule

Each aggregation table uses 2 indicators for defining a high level indicator. Each associated rule has 2 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 \wedge_1 (1).

$$\mu(L_i, L_j) = \mu_x(L_i) \wedge_1 \mu_y(L_j) \quad (1)$$

Several operators of intersection may be used: *min*, *product*, etc.

3.1.4. Fuzzy implication

As proposed by Zadeh (1975), the “if... then...” meta-implication could be viewed as a fuzzy relation. 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 $R_{i,j,k}$. $\mu(L_i, L_j, L_k)$ can be derived from $\mu(L_i, L_j)$ and from $\mu_\Gamma(i, j, k)$ (weight of the rule $R_{i,j,k}$) by means of an intersection operator, denoted \wedge_2 (e.g.: *min* operator or *product* operator):

$$\mu(L_i, L_j, L_k) = (\mu(L_i, L_j)) \wedge_2 \mu_\Gamma(i, j, k) \quad (2)$$

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

$$\mu(L_i, L_j, L_k) = (\mu(L_i) \wedge_1 \mu(L_j)) \wedge_2 \mu_\Gamma(i, j, k) \quad (3)$$

3.1.5. Aggregating the results of several rules

The 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 \perp :

$$\mu(L_k) = \perp_{i=1..4, j=1..4} \mu(L_i, L_j, L_k) \quad (4)$$

3.1.6. Systems of operators that will be tested

Table 1 presents three possible systems of operators that will be tested.

Table 1. THREE POSSIBLE SYSTEMS OF OPERATORS

Systems	Combination of premises $\mu \wedge_1 \mu'$	Implication $\mu \wedge_2 \mu'$	Aggregation of rules $\mu \perp \mu'$
Min-Max	$\min(\mu, \mu')$	$\min(\mu, \mu')$	$\max(\mu, \mu')$
Min-Sum	$\min(\mu, \mu')$	$\min(\mu, \mu')$	$\min(1, \mu + \mu')$
Prod-Sum	$\mu \times \mu'$	$\mu \times \mu'$	$\min(1, \mu + \mu')$

3.2 Issues related to the fusion of data: types of reasoning

Grabisch *et al.* (1998) or Bloch and Hunter (2001) have discussed the issue of aggregating complementary information or assessments. Possible aggregation operators may be classified into several categories: conjunctive, disjunctive,

compensative, and non-compensative. Aggregation tables used in the RERAU PI processing system refer to these categories.

For some of these fusion operations a fuzzy representation appears much more convenient than 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).

In Table 2, Case 1 is an example where two sources provide conflicting conclusions: G_4 or G_3 according to source S_1 , but G_2 according to source S_2 . Combining these results (PI3) leads to 3 possible conclusions (from G_2 to G_4 !). On the contrary, Case 2 refers to a situation where the two sources provide conclusions that are reinforcing each other, towards G_3 . In this type of situation the final conclusion will be a higher membership value associated to the common conclusion (G_3).

Table 2. TWO EXAMPLES WHERE TWO SOURCES S_1 AND S_2 ARE COMBINED TO ASSESS A RESULTING PI (PI3)

	$\mu_{S_1}(G_1)$	$\mu_{S_1}(G_2)$	$\mu_{S_1}(G_3)$	$\mu_{S_1}(G_4)$
Case 1: conflict				
PI1 (source S_1)			0.4	0.6
PI2 (source S_2)		1		
PI3 = PI1 \otimes PI2		0.5	0.2	0.3
Case 2: reinforcement				
PI1 (source S_1)			0.7	0.3
PI2 (source S_2)		0.3	0.7	
PI3 = PI1 \otimes PI2		0.05	0.90	0.05

5. CONCLUSIONS

Different kinds of base performance indicators have been inventoried, depending on the means to acquire information, and sources of uncertainty have been identified. PIs resulting from CCTV reports may require fuzzy modelling in order to control and identify misclassification error associated to sewer segment condition grading. This paper provides a way of combining PIs in

taking account the imperfection of available data (imprecise or uncertain data) and in modelling various types of reasoning such as the combination of conflicting or reinforcing indicators. Fuzzy assessment of sewer segments allows managing with imperfect information and knowledge (contradictory expert assessments, etc.); fuzzy modelling offers a way to control misclassification errors both at the scale of the asset stock and at the scale of the sewer segment. Next steps will be to calibrate fuzzy cut-off thresholds from experts' judgment for each base PI and fuzzy rules for each composite PI or rehabilitation criterion.

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