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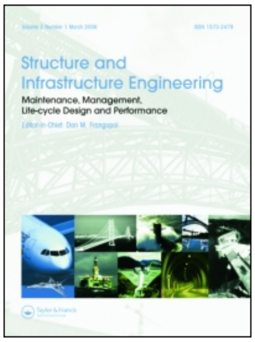

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Evaluation of uncertainties in sewer condition assessment

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ABSTRACT

Closed Circuit Television Inspection is used since decades as industry standard for sewer system inspection and structural performance evaluation. In current practice, inspection data are helpful to support asset management decisions. However, the quality and uncertainty of sewer condition assessment is rarely questioned. This article presents a methodology to determine the probability to underestimate, overestimate or accurately estimate the real condition of a pipe using visual inspection. The approach is based on the analysis of double inspections of the same sewer pipes and has been tested using the extensive data-set of the city of Braunschweig in Germany. Results indicate that the probability to inspect correctly a pipe in poor condition is close to 80%. The probability to overestimate the condition of a pipe in bad condition (false negative) is 20% whereas the probability to underestimate the condition of a pipe in good condition (false positive) is 15%. Finally, sewer condition evaluation can be used to assess the general condition of the network with an excellent accuracy probably because the respective effects of false positive and false negative are buffered.

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Introduction

Sewer asset management can be defined as managing infrastructure capital assets to minimise the total cost of owning and operating them, while delivering the service levels customers desire (EPA, 2002). A key element of asset management programmes is an efficient rehabilitation and replacement strategy. Technical needs for sewer replacement are evaluated mainly based on the structural and the hydraulic performance of the network, the structural performance being the most dominant aspect for budget allocation (van Riel, Langeveld, Herder, & Clemens, 2014). (van Riel, van Bueren, Langeveld, Herder, & Clemens, 2016) analysed the information sources of 150 sewer replacement projects in the Netherlands; the main information used by operators was found to be Closed Circuit Television Inspection (CCTV) in 60% of the cases, followed by pipe age (30% of the cases), planning of urban development and road works (45% of the cases). Several sources of information are mostly considered by the operators to plan rehabilitation actions (e.g. CCTV and opportunity of road works).

CCTV is used since decades as industry standard for sewer system inspection and structural performance evaluation. It provides visual data (images or videos) of the internal surface of the inspected pipe (in the following, the term 'pipe' indicates a pipe segment from manhole to manhole). The analysis of the image enables to identify the type and location of defects like offset joints, pipe cracks, leaks, sediment, debris and root intrusion. Generally the camera is mounted on a tractor or crawler, which enables the camera system to drive through the sewer pipe and record the entire pipe section. The main limitation of CCTV inspection is that it only provides a visual representation of the interior pipe surfaces; it cannot assess external voids, deteriorated bedding conditions, pipe wall integrity and mechanical strength. Despite these drawbacks and because of the lack of alternative cost effective inspection technology, CCTV is the state-of-the-art technology commonly used by sewer operators to assess sewer structural condition and plan rehabilitation programmes.

Only few legal requirements exist regarding sewer inspection frequency worldwide. In France each utility decides the annual inspection needed for its asset. In Germany, local regulations commit sewer operators to inspect their network regularly. Inspection frequency is defined in the self-monitoring ordinance of each region. For example, operators in North Rhine-Westphalia have to inspect their entire network within 15 years and at least 5% of the network each year (SüwVO Abw, 2013). In most countries, pipe defects recorded during CCTV inspections are manually coded according to standard coding systems and the overall sewer condition is assessed using an automatic classification methodology (Figure 1).

Sewer defect coding

The defect codification is the documentation of the CCTV inspected sewer. It is performed manually by the inspection staff. It describes the inspected sewer defects with standard codes and asset information. In Europe, the current codification system is the normative EN 13508-2 (2011) for visual inspection. Observed

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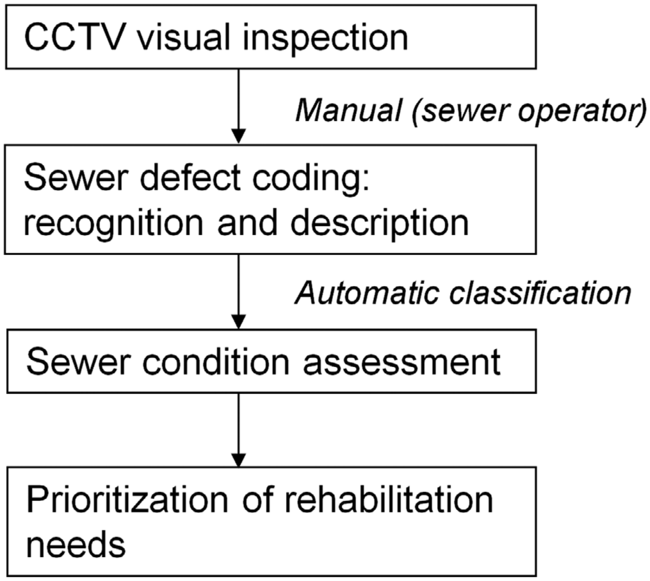

Figure 1. Workflow describing the sewer condition assessment procedure as basis for the prioritisation of sewer rehabilitation.

defects are coded with letters on three positions and a numerical value is added to quantify the defect. The first position indicates the main code (up to three letters) that describes the observed defect (e.g. BAB for crack and BBF for infiltration). The second and third positions can be used to indicate the defect characterisation (e.g. open crack in longitudinal direction). Due to the labour-intensive and error-prone manual detection and interpretation of pipe defects, recent research projects have intended to automate this procedure (Halfawy & Hengmeechai, 2014; Müller & Fischer, 2007). The proposed approaches are not commonly used by municipalities because they were not successful enough or not fully validated using visual data acquired from actual sewer inspections (Guo, Soibelman, & Garrett, 2009).

Sewer condition assessment

The primary interest of condition assessment methodologies is to transfer the extensive amount of visual inspection data into an easily manageable condition class, useful to support asset management. Many methodologies exist for sewer condition classification: e.g. RERAU in France; SRM in the UK; PACP in the US; DWA M149-3 in Germany (see Kley, Kropp, Schmidt, & Caradot, 2013; for a review of sewer classification methods and see Appendix 1 for an example of classification method). These methodologies typically use algorithms to assess the importance of each sewer defect and aggregate them in order to obtain an assessment of the overall condition of each inspected pipe for different requirements (e.g. structural and operational condition). Such condition can be directly used or can be combined with complementary performance indicators (Le Gauffre et al., 2007) to prioritise rehabilitation needs and support the definition of rehabilitation programmes.

Uncertainties in sewer condition assessment

In current practice, CCTV data are crucial to support asset management decisions. However, the quality and uncertainty of sewer condition assessment is rarely questioned. (Dirksen et al., 2013) published a comprehensive analysis of the accuracy and reliability of data obtained from visual sewer inspection. The authors highlighted the high subjectivity of the inspection procedure at three main steps:

(1) the recognition of defects,
(2) the description of defects and
(3) the evaluation of sewer condition.

It was found that the probability that an inspector fails to recognise the presence of a defect (FN) is significantly higher than the probability that a defect is reported although it is not present (FP). The probability of a FP is in the order of a few percent whereas the probability of a FN is in the order of 25%. The probability of an incorrect observation using the norm EN 13508-2 for all defects was over 50% for defect recognition and description. Further it was shown that individual inspectors arrive at different results when evaluating a given set of CCTV data, thereby highlighting the subjectivity of interpreting images.

Hüben (2002) analysed condition classes from repeated inspections of a German city. The results showed that over 50% of the sewers changed of condition classes between the repeated inspections. He concluded that the uncertainties in the defect recognition and description are propagated in the assessment of the sewer condition class and significantly influence the results. (Sousa, Ferreira, Meireles, Almeida, & Matos, 2014) also quantified CCTV uncertainties by comparing periodic inspection reports from three trunk sewers of a Portuguese sewer system. Over 25 km of inspected pipes, 25% of the sewer pipes had different structural condition ratings between the repeated inspections. The authors highlighted a high degree of consistency of the inspectors regarding the most severe defects.

The uncertainties at each step of the sewer condition assessment procedure have been described in the mentioned references. However the limited literature on the subject concerns uncertainty in the recognition and description of individual defects and does not address the whole evaluation process (Figure 1). There is still a need to assess sewer condition uncertainty as a whole by considering the propagation of each source of uncertainty. This is a major step in order to be able to assess the influence of sewer condition uncertainties in asset management decisions and predictive deterioration models. In this article, the uncertainty of the whole process (from CCTV inspection to condition assessment) is addressed and quantified, using condition evaluation of double inspections of the same pipes. The aim is to determine the probability to underestimate, overestimate or accurately estimate the real condition of a pipe using CCTV inspection.

Methodology

List of notations

Name	Description	Status
N_{ij}	Number of pipes inspected twice, first in condition i and then in condition j	Known
N	$N = \{N_{ij}\}$ matrix 4×4	
$\sum N_{ij}$	Number of inspected pipes twice	
Ri	Number of pipes really in condition i	Unknown

Name	Description	Status
R	$R = \{R_1, R_2, R_3, R_4\}$ vector	Unknown
$P(\beta = i)$	Probability for a pipe to be inspected in condition i	Unknown
$P(\alpha = i)$	Probability for a pipe to be really in condition i	Unknown
$P(\beta = i\|\alpha = j)$	Probability for a pipe to be inspected in condition i when really in condition j	Unknown
P	$P = \{P(\beta = i\|\alpha = j)\}$ 4×4 matrix	
$P(\alpha = i\|\beta = j)$	Probability to be really in condition i when inspected in condition j.	Unknown
Q	Uncertainty 4×4 matrix $Q = \{P(\alpha = i\|\beta = j)\}$	
$N_{\text{estimated}}$	$N_{\text{estimated}} = \{N_{\text{estimated } i,j}\}$ Estimated double inspection matrix	Unknown

General concept

Let's assume that each inspected pipe has a *real* structural condition that described the rehabilitation needs. The *real* condition is defined as the sewer internal condition that would lead to the best rehabilitation decision. The *real* condition of the pipe is unfortunately unknown. The best estimation of the *real* condition of a pipe would be the average internal condition (or mode) obtained with a high (infinite) number of repeated CCTV inspections. In practice it is impossible to be sure to estimate correctly the real condition of a pipe since there is no warranty that a pipe inspected twice (or even three or four times) in the same condition has been correctly inspected. Even if the inspected conditions are consistent, they can be consistently wrong.

The *real* condition of the pipe can be estimated with an *inspected* condition, following the steps of CCTV visual inspection, sewer defect coding and sewer condition assessment (Figure 1). The *inspected* condition might estimate correctly the *real* condition but can also underestimate or overestimate the *real* condition since uncertainties affect each step of the condition assessment procedure. The main aim of the analysis is to determine the uncertainty matrix Q:

$$Q = \{P(\alpha = i|\beta = j)\} \tag{1}$$

The probability $P(\alpha = i|\beta = j)$ expresses the probability to be really in condition i when inspected in condition j. The term α indicates the real condition of a pipe (which is unknown). The probability for a pipe to be really in condition i is given by $P(\alpha = i)$. The term β indicates the inspected condition of a pipe (which is known). The probability for a pipe to be inspected in condition j is given by $P(\beta = j)$. To simplify the further development we consider four condition classes only, 4 being the worst condition indicating an urgent rehabilitation need.

$$i, j \in \{1, 2, 3, 4\}$$

The probability $P(\alpha = i|\beta = j)$ is illustrated by the decision tree in Figure 2.

P: inverse uncertainty matrix

The inverse uncertainty matrix $P = \{P(\beta = i|\alpha = j)\}$ contains the inverse conditional probabilities of the matrix Q and is illustrated by the decision tree in Figure 3. P gives the probability to be inspected in condition i when a pipe is really in condition j:

$$P = \begin{vmatrix} P(\beta = 1|\alpha = 1) & P(\beta = 1|\alpha = 2) & P(\beta = 1|\alpha = 3) & P(\beta = 1|\alpha = 4) \\ P(\beta = 2|\alpha = 1) & P(\beta = 2|\alpha = 2) & P(\beta = 2|\alpha = 3) & P(\beta = 2|\alpha = 4) \\ P(\beta = 3|\alpha = 1) & P(\beta = 3|\alpha = 2) & P(\beta = 3|\alpha = 3) & P(\beta = 3|\alpha = 4) \\ P(\beta = 4|\alpha = 1) & P(\beta = 4|\alpha = 2) & P(\beta = 4|\alpha = 3) & P(\beta = 4|\alpha = 4) \end{vmatrix} \tag{2}$$

To simplify the writing, P is expressed as:

$$P = \begin{vmatrix} P11 & P12 & P13 & P14 \\ P21 & P22 & P23 & P24 \\ P31 & P32 & P33 & P34 \\ P41 & P42 & P43 & P44 \end{vmatrix} \tag{3}$$

It is assumed that P is an unknown constant and corresponds to the average uncertainty of the condition assessment procedure. This assumption is required because some factors that are known to influence the inspection results are not available. Visual inspection can be influenced by the experience of the operator and his age/sex/education (Hassan & Diab, 2010; Heidl, Thumfart, Lughofer, Eitzinger, & Klement, 2013; Laofor & Peansupap, 2012); and by the condition of the investigation such

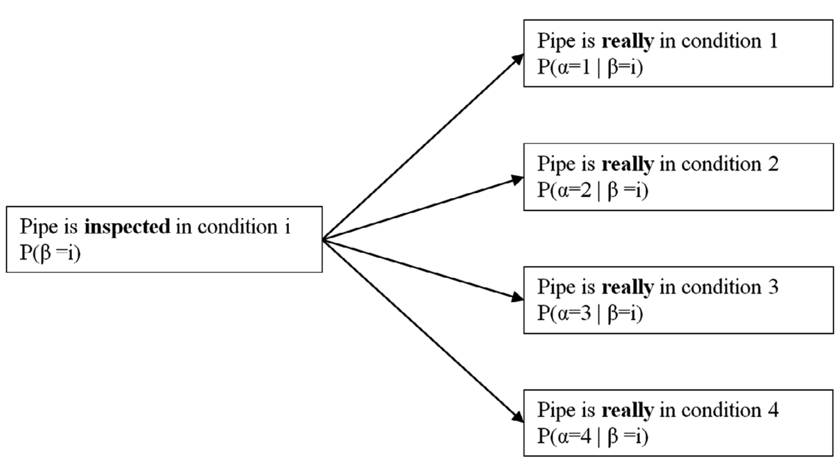

Figure 2. Decision tree for $P(\alpha = i \mid \beta = j)$.

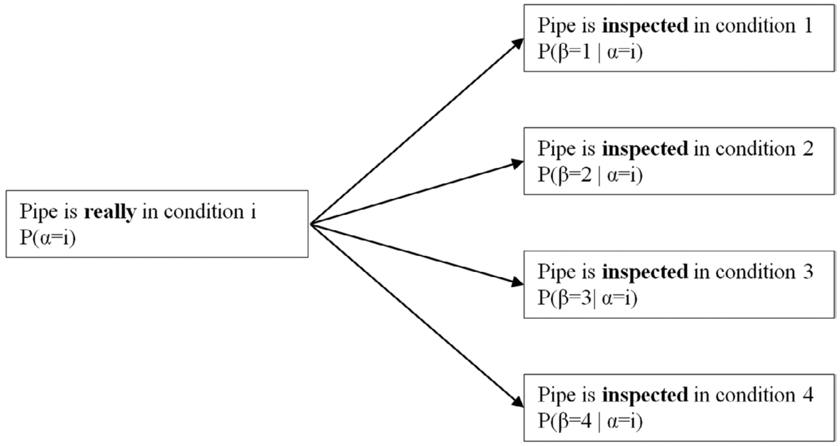

Figure 3. Decision tree for $P(\beta = i \mid \alpha = j)$.

as equipment used (Plihal, Kuratko, & Ertl, 2014), cleaning condition, lightning, disturbances (Gramopadhye & Wilson, 1997).

R: number of pipes really in each condition

From a set of inspected pipes, the unknown number of pipes really in each condition is expressed as:

$$R = \begin{vmatrix} R1 \\ R2 \\ R3 \\ R4 \end{vmatrix} \tag{4}$$

N: number of pipes inspected twice, first in condition i and then in condition j

From the inspection database, if several pipes have been inspected twice, we can create the double inspection matrix N such as $N = \left\{ N_{ij} \right\}$. Each cell of the matrix contains the number of pipes inspected twice, first in condition class i and then in condition class j. We assume a short period between the repeated inspections so we can neglect sewer deterioration: in this case the matrix is (almost) symmetric and the repeated inspections are considered independent:

$$N_{ij} = N_{ji} \tag{5}$$

$$N = \begin{vmatrix} N11 & N21 & N31 & N41 \\ N12 & N22 & N32 & N42 \\ N13 & N23 & N33 & N43 \\ N14 & N24 & N34 & N44 \end{vmatrix} = \begin{vmatrix} N11 & - & - & - \\ N12 & N22 & - & - \\ N13 & N23 & N33 & - \\ N14 & N24 & N34 & N44 \end{vmatrix}$$

Relation between N, R and P

The values N_{ij} can be estimated using P and R with the following expression:

$$\begin{aligned} N_{ij} \cong\ & R1.P\left(\beta = i|\alpha = 1\right).P\left(\beta = j|\alpha = 1\right) \\ & + R2.P\left(\beta = i|\alpha = 2\right).P\left(\beta = j|\alpha = 2\right) \\ & + R3.P\left(\beta = i|\alpha = 3\right).P\left(\beta = j|\alpha = 3\right) \\ & + R4.P\left(\beta = i|\alpha = 4\right).P\left(\beta = j|\alpha = 4\right) \end{aligned} \tag{6}$$

The number of pipes inspected first in condition i and then in condition j is equal to the number of pipes in every condition inspected first in condition i and then in j. Consequently, a system of 10 equations is formulated: 16 equations in total but since the matrix is symmetric 6 equations are double. The system is composed of 20 variables with 15 degrees of freedom.

- $R4$ can be estimated from $R1$, $R2$ and $R3$ as well as from the number of inspected pipes $\sum N_{ij}$. R has 4 variables with 3 degrees of freedom:

$$R4 = \sum N_{ij} - R1 - R2 - R3 \tag{7}$$

- P can be estimated by knowing the 3×4 upper part of the matrix since the sum of columns is equal to 1. P has 16 variables with 12 degrees of freedom. If a pipe is really in condition i, it will necessarily be inspected in condition 1, 2, 3 or 4:

$$\begin{aligned} & P\left(\beta = 1|\alpha = i\right) + P\left(\beta = 2|\alpha = i\right) \\ & \quad + P\left(\beta = 3|\alpha = i\right) + P\left(\beta = 4|\alpha = i\right) = 1 \end{aligned} \tag{8}$$

Resolution of the system of nonlinear equations

The system of 10 equations and 15 parameters is resolved using the global optimisation method ISRES - Improved Stochastic Ranking Evolution Strategy (Runarsson & Yao, 2005). ISRES is available for different programming languages in the open-source library NLopt for nonlinear optimisation (Johnson, 2014). This method has been chosen for being a derivative-free optimisation (no need to assess the gradient of the optimisation function) and for supporting bound constraints as well as nonlinear inequality constraints. The nonlinear optimisation method minimises an objective function defined as the difference between the observed double inspections matrix and its estimation:

$$\min \sum \left(N_{ij} - N_{\text{estimated } i,j}\right)^2 \tag{9}$$

The method identifies the set of parameters that minimise the objective function i.e. that allow the most accurate estimation of the double inspection matrix $\left\{ N_{ij} \right\}$.

The 15 parameters are $P11$, $P12$, $P13$, $P14$, $P21$, $P22$, $P23$, $P24$, $P31$, $P32$, $P33$, $P34$, $R1$, $R2$ and $R3$. The parameters constraints are defined as follows:

- $P_{ij} \in [0,1]$ – Probabilities vary from 0 to 1,
- $P_{ii} > P_{ji}$ – Probabilities to be inspected in the right condition is higher than the probability to be inspected in a wrong condition,
- $R_i \in \left[0, \sum N_{ij}\right]$ – The number of pipes in each condition is smaller than the total number of pipes.

The optimisation is run 50 times using a Monte-Carlo simulation with a random selection of the starting parameter values within the defined constraints field. The Monte-Carlo simulation aims at assessing the influence of the starting values on the stability of the results.

Calculation of the probabilities of false positive and false negative

The matrix P is used to determine the probabilities of false positive and false negative by inspecting a pipe in a given condition. A false negative (FN) occurs when the inspected condition overestimates the real condition: the inspected condition is better than the real condition (e.g. defects are actually present but have been missed by the operator). A false positive occurs (FP) when the inspected condition underestimates the real condition: the inspected condition is worse than the real condition (e.g. the operator exaggerates the size of a crack):

$$P(FN|\alpha = i) = \sum_j P(\beta = j|\alpha = i) \, with \; j < i \tag{10}$$

$$P(FP|\alpha = i) = \sum_j P(\beta = j|\alpha = i) \, with \; j > i \tag{11}$$

Calculation of Q

The optimisation procedure calculates R and P but the final objective is to estimate $Q = \{P(\alpha = i|\beta = j)\}$. Q and P are linked by the Bayes' theorem:

$$P(\alpha = j|\beta = i) = \frac{P(\beta = i|\alpha = j).P(\alpha = j)}{P(\beta = i)} \tag{12}$$

$$P(\alpha = j) = \frac{Rj}{\sum Ri} \tag{13}$$

The probability to be inspected in the real condition j is equal to the number of pipes really in condition j divided by the number of pipes.

$$\begin{aligned} P(\beta = i) &= P(\alpha = 1).P(\beta = i|\alpha = 1) + P(\alpha = 2).P(\beta = i|\alpha = 2) \\ &\quad + P(\alpha = 3).P(\beta = i|\alpha = 3) + P(\alpha = 4).P(\beta = i|\alpha = 4) \\ &= \{P(\alpha = 1), P(\alpha = 2), P(\alpha = 3), P(\alpha = 4)\}.P[i,] \end{aligned} \tag{14}$$

The matrix $Q = \{P(\alpha = i|\beta = j)\}$ can be used to assess the probability to be really in condition i when inspected in condition j.

Data description

This study has been performed using the CCTV database of the city of Braunschweig in Germany (250,000 inhabitants).

Sewer characteristics

The sewer network of Braunschweig has a length of about 1,800 km with about 45,000 pipe segments. The sewer system is mostly separated: 52% of the pipes are stormwater sewers whereas 41% are sanitary sewers and 7% are combined sewers. Clay and concrete are the two dominating materials with a share of more than 90%. Almost every sanitary pipe is constructed with clay (99%) whereas most stormwater pipes are made of concrete and reinforced concrete (99%).

CCTV inspection

CCTV inspections have been carried out for decades using an adaptation of the German standard ATV-M 143-2 (1999) for defect coding. Data has been stored systematically in a database since 1998. All pipes have been inspected at least once. The total number of available CCTV inspections is 69,384. Inspections with inconsistent defect coding, without age (inspection year or construction year is missing) or that could not be linked to a specific sewer pipe have been discarded from the database. After the data clean-up, the database contains 45,049 inspections with an inspected length of 1,784 km. Figure 4 shows the number of pipes inspected every year and Figure 5 shows the number of inspections per pipe. Almost 50% of the pipes have been inspected at least twice.

Figure 6 shows the distribution of durations between the repeated inspections. According to the local regulation, the entire network must be inspected every 10 years; indeed most second inspections have been performed between 8 and 10 years after the first inspection.

Sewer condition assessment

The structural condition class of the inspected pipes is evaluated using an adaptation of the French classification methodology RERAU (based on dysfunction 'COL' indicating the risk of collapse; see Ahmadi et al., 2014; Le Gauffre, Joannis, Breysse, Gibello, & Desmulliez, 2004). The aim of this methodology is to rank inspected sewer pipes based on the urgency of their rehabilitation needs. A structural condition class is assigned to each sewer segment (from manhole to manhole) on a four-grade scale (1–4, 4 being the worst condition and in need for immediate rehabilitation). The structural condition class is calculated using the characterisation and quantification of sewer defects such as fissures, corrosion and surface damages that may lead to structural failure such as a pipe collapse. The method is presented in Appendix 1.

The matrix of double inspection shows the number of pipes inspected first in condition i and then in condition j and can be expressed as:

$$N = \begin{vmatrix} 6125 & 484 & 644 & 106 \\ 1295 & 774 & 459 & 121 \\ 1190 & 502 & 1681 & 298 \\ 407 & 318 & 599 & 659 \end{vmatrix}$$

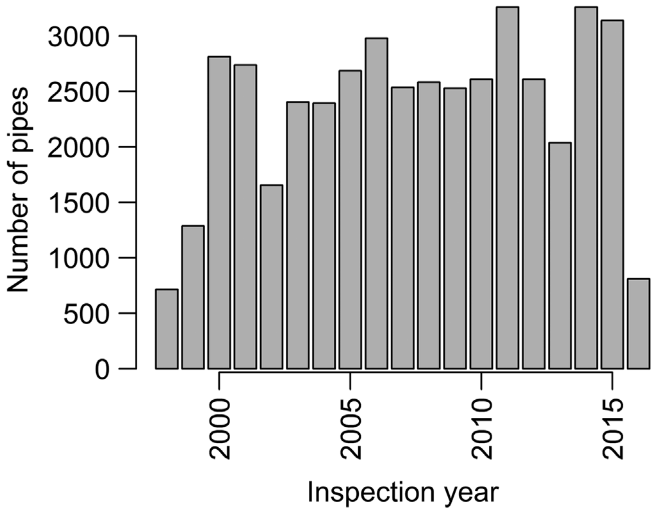

Figure 4. Number of pipes inspected every year.

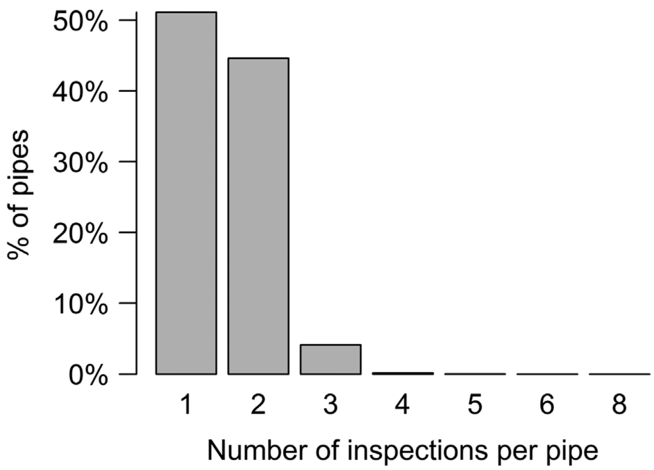

Figure 5. Proportion of pipe vs. number of inspections per pipe.

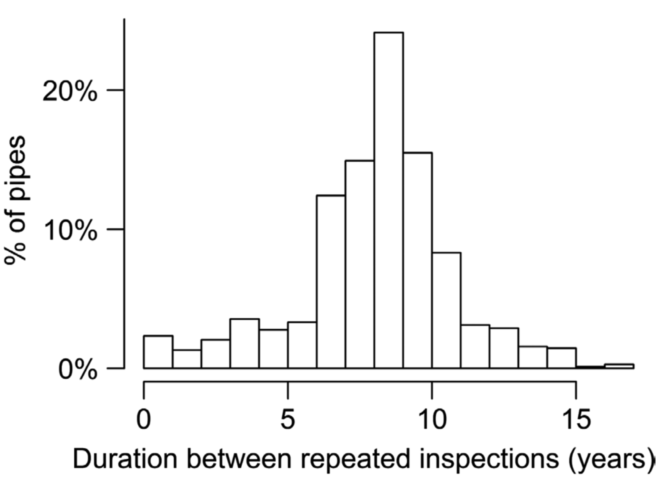

Figure 6. Percentage of pipes for different years between inspections.

It is relevant to note that the down part under the diagonal is higher than the upper part. For example, 1,295 pipes have been inspected first in condition 1 and then in condition 2 but only 484 pipes have been inspected first in 2 and then in 1. This behaviour is linked with the deterioration process between the repeated inspections. Most pipes have been inspected the second time more than 8 years after the first inspections and many of them switched in between to the next worst condition class.

Three reasons can explain a condition transition between first and second inspections: (i) the condition of the second inspection is worst due to degradation; (ii) the condition of the second inspection is better due to rehabilitation; (iii) the condition has changed due to uncertainties in the condition assessment procedure. In order to observe the transitions due to uncertainties only, the pipes that undergo a condition transition due to reason (i) or (ii) must be removed from the database. Rehabilitated pipes have already been filtered out by preparing the data-set. In order to remove the influence of the deterioration process, the pipes with a period between repeated inspections higher than 3 years have been also filtered out. Considering the life duration of the pipes, we assume that the probability to observe a condition transition due to degradation within three years is not significant:

$$N = \begin{vmatrix} 340 & 39 & 48 & 18 \\ 38 & 37 & 24 & 9 \\ 45 & 33 & 111 & 27 \\ 13 & 10 & 28 & 71 \end{vmatrix}$$

The obtained matrix is almost symmetric: the average deviation between the down and upper part is small (11%) which indicates that the deterioration is not relevant any more or less relevant than the uncertainty related to the inspection. Different periods have been tested (from 10 years to one year). Within a period of 3 years we can assume that the deterioration is insignificant and that two inspections of a same pipe are independent: the number of pipes inspected first in *i* and then in *j* is similar to the number of pipes inspected first in *j* and then in *i*. Higher periods do not give such symmetrical matrix, and with a period smaller than 3 years, the matrix remains symmetric but the number of pipes becomes far too small to run the analysis. In order to apply the methodology the matrix is forced to be symmetric. The mean of the down and upper parts of the original matrix is computed and used to replace both down and upper parts:

$$N = \begin{vmatrix} 340 & 38 & 46 & 16 \\ 38 & 37 & 28 & 10 \\ 46 & 28 & 111 & 28 \\ 16 & 10 & 28 & 71 \end{vmatrix}$$

The number of pipes with differences between structural condition classes is presented in Figure 7. About 65% of the pipes have been inspected twice in the same conditions whereas 35% of the pipes have a different condition between the repeated inspections.

Discussion of the results

The optimisation method has been applied on the double inspection matrix N. Table 1 and Figure 8 illustrate the calculated mean and standard deviations of P, R and $N_{\text{estimated}}$. The optimisation procedure was successful. For each Monte-Carlo run, the objective function converged towards 0 ($<10^{-5}$) so $N = N_{\text{estimated}}$, independently from the parameter starting values. The standard deviation of the obtained parameters P and R is relatively

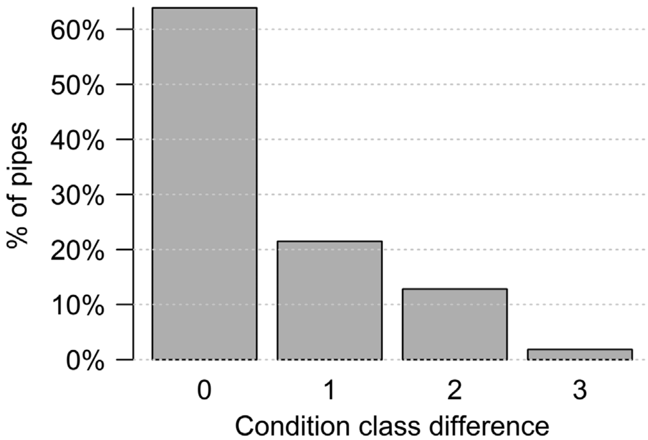

Figure 7. Percentage of pipes with differences between the structural condition classes.

low indicating that the optimisation procedure finds a global optimum instead of multiple local optimums. P has been used to compute the probabilities of false positive and false negative with Equations (10) and (11) (Table 2). Finally the parameters P and R have been used to derive Q with Equation (12) (Table 3).

Several outcomes can be highlighted:

- The probability to be inspected in the right condition (P_{ii}) is higher for pipes in good condition (probability of 84.5% for pipes in condition 1) than for pipes in poor condition (probability of 79.1% for pipes in condition 4). It indicates that there is less uncertainty by assessing the condition of sewers with few defects only or without severe defects. This is an expected outcome: the inspectors that perform the defect coding are more prone to error when many defects are present as when sewers are in perfect condition.
- The probability to be inspected correctly in condition 2 is only 58.8% indicating high uncertainties especially for this condition class. This might be explained by the fact that only a few pipes are in condition 2 compared to pipes in condition 1 and 3. The condition classification method uses fine thresholds to separate conditions 1, 2 and 3. Given the high uncertainties in identifying pipes in condition 2, this condition might be merged with condition 1 without losing information.
- The probability to be inspected correctly in condition 4 is 79.1%. It means that there is a probability of 20.9% to be wrong by overestimating the real condition of the pipe (FN). FN errors can have major consequences due to the fact that major defects leading to failure or collapse might be missed (Ahmadi et al., 2014). Since rehabilitation programmes are based on structural condition evaluation, the influence of this uncertainty on rehabilitation decisions remains to be evaluated.
- For each condition (except condition 2 that have few pipes only), the probability of FN is significantly higher than the probability of FP. It means that the probability to overestimate the condition of a pipe is higher than the probability to underestimate its condition. (Dirksen et al., 2013) found out that the probability that the inspector fails to recognise the presence of a defect is significantly higher than the probability that a defect is reported although it is not present: FN was in the order of 25% whereas FP in the order of few percent. Looking to condition assessment in this study, the probability of FN for a pipe in bad condition 4 is 20.9% whereas but the probability of FP for pipes in good condition 1 is 15.5%. The only high FP value is obtained for condition 2 which is the most uncertain condition given the limited number of pipes in this class.
- The probability to be inspected in a given condition $\{P(\beta = i)\}$ is very similar to the probability to be really in this condition $\{P(\alpha = i)\}$ (Figure 9). It means that at the network level the number of pipes really in each condition is similar to the number of pipes inspected in each condition. The evaluation of sewer condition at the pipe level is biased since FN is higher than FP. However the evaluation of the condition distribution at the network level is not biased anymore, probably because the respective effects of FP and FN are buffered. This is a promising

Table 1. Outcomes (mean and standard deviation SD) from the optimisation procedure with 50 Monte-Carlo simulations.

P: inverse uncertainty matrix

$$\mathrm{mean}(P) = \begin{vmatrix} 84.5 & 14.2 & 10.1 & 5.3 \\ 6.9 & 58.8 & 9.3 & 3.3 \\ 6.7 & 18.6 & 70.1 & 12.3 \\ 2 & 8.4 & 10.5 & 79.1 \end{vmatrix} \qquad \mathrm{SD}(P) = \begin{vmatrix} 3.3 & 7.7 & 6.9 & 2.9 \\ 1.2 & 8.7 & 4.6 & 2.3 \\ 2.7 & 10.4 & 6.4 & 3.8 \\ 0.7 & 3.6 & 2.8 & 1.8 \end{vmatrix}$$

R: number of pipes really in each condition

$$\mathrm{mean}(R) = \begin{vmatrix} 469 \\ 101 \\ 213 \\ 108 \end{vmatrix} \qquad \mathrm{SD}(R) = \begin{vmatrix} 42 \\ 36 \\ 46 \\ 5 \end{vmatrix}$$

N: number of pipes inspected twice, first in condition i and then in condition j

$$\mathrm{mean}\left(N_{\mathrm{estimated}}\right) = \begin{vmatrix} 340 & 38 & 46 & 16 \\ 38 & 37 & 28 & 10 \\ 46 & 28 & 111 & 28 \\ 16 & 10 & 28 & 71 \end{vmatrix} \qquad \mathrm{SD}\left(N_{\mathrm{estimated}}\right) = \begin{matrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{matrix}$$

$$N - N_{\mathrm{estimated}} = \begin{matrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{matrix}$$

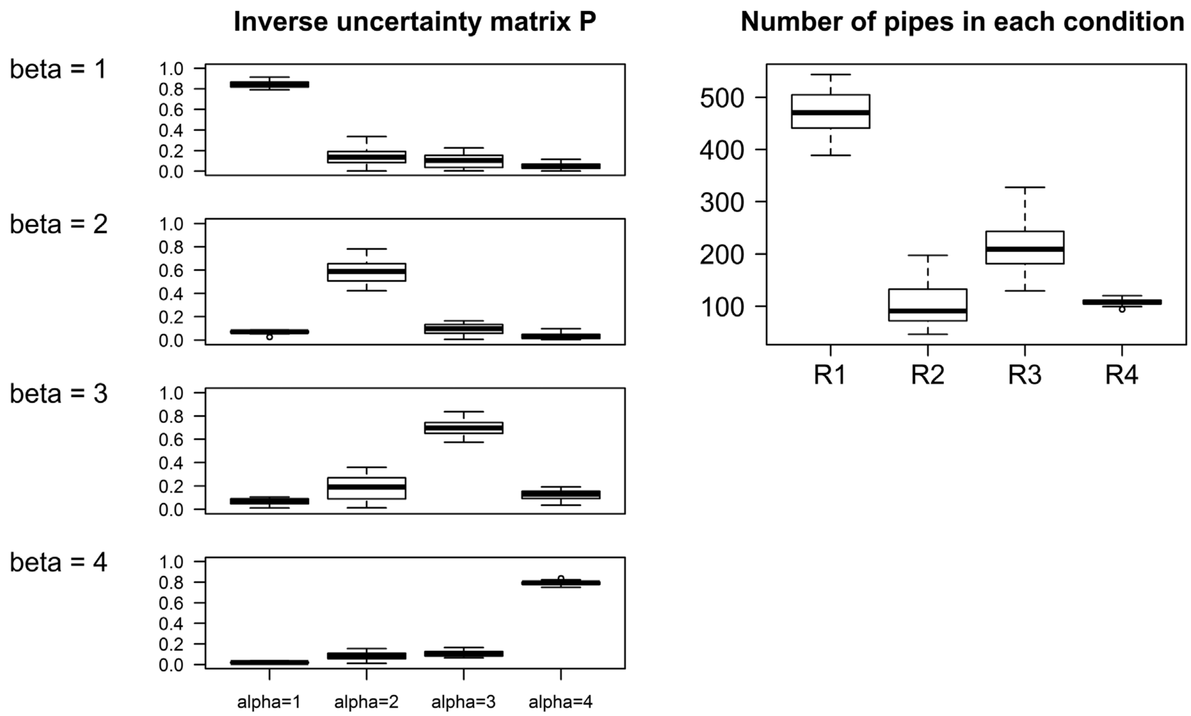

Figure 8. Deviations of P and R from 50 Monte-Carlo simulations; the left graphs plot the values of the four rows of the matrix P.

Table 2. Calculation of FP and FN for sewer condition assessment (in %); the condition ranges from 1 to 4, 4 being the worst condition indicating an urgent rehabilitation need.

	Real condition i				
	1	2	3	4	
$P(FN\|\alpha = i)$	–	14.2	19.4	20.9	Inspected condition is better as the real condition
$P(\beta = i\|\alpha = i)$	84.5	58.8	70.1	79.1	Inspected condition is the real condition
$P(FP\|\alpha = i)$	15.5	27	10.5	–	Inspected condition is worst as the real condition

Table 3. Calculation of Q.

Probability to be really in condition i $\{P(\alpha = i)\} = \begin{vmatrix} 52.7 \\ 11.3 \\ 23.9 \\ 12.2 \end{vmatrix}$

Probability to be inspected in condition i $\{P(\beta = i)\} = \begin{vmatrix} 49.2 \\ 12.9 \\ 23.8 \\ 14.1 \end{vmatrix}$

Probability to be really in condition i when inspected in j

$$Q = \{P(\alpha = i|\beta = j)\} = \begin{vmatrix} 90.5 & 28.2 & 14.7 & 7.4 \\ 3.3 & 51.5 & 8.8 & 6.7 \\ 4.9 & 17.2 & 70.2 & 17.8 \\ 1.3 & 3.1 & 6.3 & 68 \end{vmatrix}$$

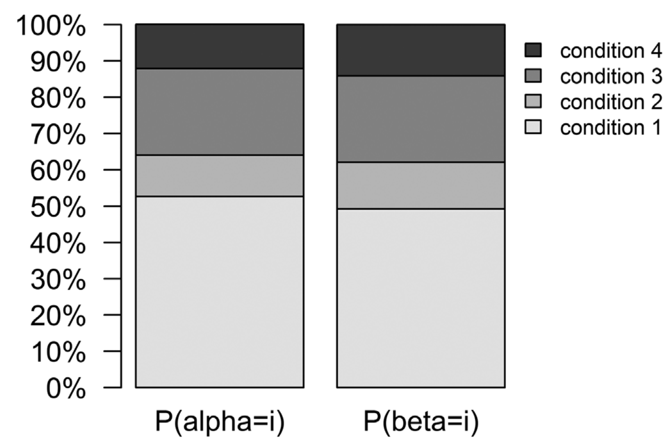

Figure 9. Probabilities to be really in each condition and to be inspected in each condition; 4 is the worst condition displayed in dark colour.

outcome indicating that inspection data can be used to assess the general condition of the network with an excellent accuracy.

- Finally, the matrix Q can be used to assess the uncertainty of inspection results (Table 3). When a pipe is inspected in bad condition 4, the probability to be really in condition 4 is 68%. There is thus a significant probability of 32% to be wrong by underestimating the real condition of the pipe (the inspection indicates condition 4 but the real condition is 1, 2 or 3). On the other hand if the pipe is inspected in good condition 1 there is a high probability of 90.5% that the pipe is actually in good condition. These results underline the high uncertainties related to pipes inspected in bad condition. They can be used to propagate uncertainties in sewer deterioration model and assess the influence of sewer condition uncertainties in asset management decisions.

It is worth noting that these results describe the average uncertainty of sewer condition assessment. The condition assessment is far to be a homogeneous procedure with standard operating conditions. Several factors might influence the outcome: e.g. the operator skills, the inspection velocity, the light and cleaning quality, the resolution of the CCTV camera, etc. Further research might focus on the evaluation of uncertainty for specific operational conditions or highlight the factors that have most influence on the accuracy of sewer condition assessment.

Conclusions

This study introduced and demonstrated a methodology based on double inspections of the same pipes to determine the uncertainties of the structural condition assessment, i.e. the probability for a pipe of being really in a given structural condition when inspected in a given structural condition. The methodology is based on a nonlinear optimisation procedure coupled with a Monte-Carlo simulation and has been used to determine the probabilities of false positive and false negative by inspecting a pipe in a given condition.

This study has been performed using the extensive CCTV database of the city of Braunschweig in Germany. The structural condition class of the inspected pipes has been evaluated using an adaptation of the French classification methodology RERAU (Ahmadi et al., 2014; Le Gauffre et al., 2004) that assigns a grade from 1 to 4, 4 being the worst condition. The main outcomes are summarised below:

- The probability to inspect correctly a pipe in poor condition 4 is close to 80% and thus the probability to overestimate the condition of the pipe is close to 20%. In general, the probability to overestimate the condition of a pipe (FN) is higher than the probability to underestimate its condition (FP). For pipes in bad condition, the probability of FN is 20% whereas for pipes in good condition the probability of FP is 15%. This uncertainty might have serious consequences on rehabilitation decisions since missed defects can lead to failure or collapse. The influence of this biased information on the reliability of rehabilitation programmes and on costs is still to be investigated (on this topic see also the work of van Riel, Langeveld, Herder, & Clemens, 2017).
- At the network level, the evaluation of the condition distribution is not biased anymore: the probability for a pipe to be really in a given condition is very similar to the probability for a pipe to be inspected in a given condition. Sewer condition evaluation can be used to assess the general condition of the network with an excellent accuracy.
- Finally, when a pipe is inspected in bad condition, the probability to be really in bad condition is 68%. There is thus a significant probability to be wrong by underestimating the real condition of the pipe. The influence of this uncertainty on deterioration models outcomes needs to be carefully investigated. The uncertainty might be propagated in the models and lead to biased budget predictions (on this topic see also the work of Ahmadi, Cherqui, de Massiac, & Le Gauffre, 2015).

These results are case specific and should still be demonstrated using repeated inspections from another city. The methodology proposed could be used again to confirm these outcomes using other data but also to assess uncertainties for condition assessment of other infrastructure.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix 1: Short presentation of the adapted methodology RERAU used to assess sewer condition

The methodology assigns to each inspected pipe an integer score between 1 and 4, 4 being the worst condition indicating an immediate rehabilitation need. The score depends on the density and severity of the defects. Following the inspection of a sewer pipe, each observed defects O_i is coded following the European norm EN 13508-2. The following main codes that might influence the structural condition of the pipe are considered.

Fissure	BAB
Defective brickwork or masonry	BAD
Missing mortar	BAE
Surface damage	BAF
Break/collapse	BAC
Defective repair	BAL

- An elementary score N_i is calculated for each observed defects O_i.

$$N_i = l.G$$

  - G is a gravity parameter given by tables in Le Gauffre et al. (2004)
  - l is the length of the defect (in case of continuous defects) or the standard length parameter in case of punctual defects
- The density of defects is calculated at the pipe level considering pipe length L

$$D = \frac{\sum N_i}{L}$$

- D is compared with three thresholds S12, S23, S34 to attribute a condition class from 1 to 4 from the density value
  - Condition class 1 if D < S12
  - Condition class 2 if S12 < D < S23
  - Condition class 3 if S23 < D < S34
  - Condition class 4 if S34 < D
- Additionally, the observation of major defects can assign a condition class to the pipe directly, without calculation of the density. A table given by Le Gauffre et al. (2004) describe the direct attribution of condition classes from observed defects O_i
  - Example: condition 3 if defect BAC-A (Break with pieces of pipe visibly displaced but not missing); condition 4 if defect BAC-C (Collapse with complete loss of structural integrity)