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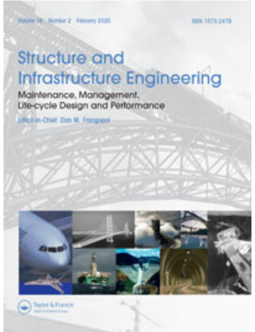

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The influence of condition assessment uncertainties on sewer deterioration modelling

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ABSTRACT

Deterioration models can be used to forecast the evolution of the condition of the sewer network under different investment strategies. Models are calibrated using condition scores obtained from sewer visual inspection. Many studies highlighted the uncertainties in the procedure of sewer condition assessment, mainly due to the subjectivity of the coding operator. However, the influence of this uncertainty on the outcomes of deterioration modelling remains unknown. This paper analyses the influence of sewer condition uncertainties on the prediction of deterioration models. An optimisation methodology has been applied to quantify uncertainties in sewer condition assessment from the analysis of a set of repeated inspections. Then, a method is proposed to propagate uncertainties in the survival curves of a deterioration model using the inspection dataset of the city of Berlin, Germany. Results indicate that old pipes in bad condition are more prone to False Negative than False Positive (higher probability to miss defects). As a result, the propagation of uncertainties leads to more pessimistic survival curves with a confidence interval of ±12% at 100 years. The analysis shows that the required replacement rate to maintain a constant network condition is underestimated if uncertainties are not considered.

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Asset management; sewer; defect; closed-circuit television (CCTV); inspection; condition assessment; uncertainty; deterioration model

1. Introduction

Sewer systems form one of the most capital-intensive infrastructure systems in cities. Managing such an infrastructure is often defined as finding the right balance over time between costs, services and risks (Burns, Hope, & Roorda, 1999; Cashman et al., 2004; Marlow et al., 2007; Parsons, 2006). For decades, sewer asset management has mainly been a 'run-to-failure' approach (Wirahadikusumah, Dulcy, & Iseley, 2001): decisions are based on practical experience and most of the operational resources are allocated to emergency rehabilitation or replacement of failed components (Ugarelli, Selseth, Le Gat, Rostum, & Krogh, 2013). In order to cope with the ongoing aging of the infrastructure and to maintain service quality, municipalities are progressively shifting to a proactive management aiming at anticipating the consequences of strategic decisions and targeting sewer segments before any failure occurs (Ahmadi, Cherqui, De Massiac, & Le Gauffre, 2014). The implementation of such an approach is usually hampered by the lack of information about assets condition, in a general context of budget limitation (Harvey & McBean, 2014).

Over the last decades, modelling has gained increasing importance into assisting proactive management due to: (1) a better data availability, (2) the possibility to relate several data sources, (3) the increase of computational power and (4) the development of operational software. Modelling tools support utilities in addressing a broad range of issues such as sewer deterioration (Ana & Bauwens, 2010; Egger, Scheidegger, Reichert, & Maurer, 2013; Kleiner, Sadiq, & Rajani, 2006; Salman, 2010), selection of rehabilitation technique (Das, Bayat, Gay, & Matthews, 2018), infiltration and exfiltration (Bertrand-Krajewski et al., 2010), flood risk (Dey & Kamioka, 2007; Yazdi, Lee, & Kim, 2015), sewer blockage (Jin & Mukherjee, 2010), sediment deposition (Ashley, Fraser, Burrows, & Blanksby, 2000; Rodríguez, McIntyre, Díaz-Granados, & Maksimović, 2012) or combined sewer overflows (Morales, Mier, & Garcia, 2017).

Deterioration models, which are in the focus of this study, can be used to simulate the condition of non-inspected sewer segments and to forecast the evolution of the condition of sewer networks under different investment strategies. Models are usually calibrated to predict sewer structural condition from a set of explanatory factors such as sewer age, material, effluent type, traffic load, etc. Model outputs provide key information to operators and municipalities for the scheduling of inspection programmes (i.e. the detection of sewers in critical condition and potentially the reduction of inspection costs by avoiding inspections of

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segments in good condition) and the planning of rehabilitation budgets (i.e. the comparison of different sewer rehabilitation scenarios and the evaluation of necessary investment rates).

Many researches have focussed on the development of statistical or machine learning deterioration models (e.g. Ana & Bauwens, 2010; Baur & Herz, 2002; Elmasry, Zayed, & Hawari, 2016; Harvey & McBean, 2014; Kley & Caradot, 2013; Le Gat, 2008; Marlow et al., 2009; Mashford, Marlow, Tran, & May, 2011; Micevski, Kuczera, & Coombes, 2002; Najafi & Kulandaivel, 2005; Salman, 2010; Tran, Ng, & Perera, 2007; Vitorino et al., 2014). Further studies have investigated the relevant explanatory factors for model calibration (e.g. Carvalho, Amado, Brito, Coelho, & Leitão, 2018; Davies, Clarke, Whiter, & Cunningham, 2001; El-Housni, Ouellet, & Duchesne, 2018). Several recent studies have focussed on quantifying different sources of uncertainties, which might affect model predictions, such as:

- the predictive performance of the model itself: Duchesne, Beardsell, Villeneuve, Toumbou, & Bouchard, 2013; Rokstad, Le Gat, & Ugarelli, 2014; Sousa, Ferreira, Meireles, Almeida, & Saldanha Matos, 2014b;
- the availability of CCTV data for model calibration: Ahmadi, Cherqui, Aubin, & Le Gauffre, 2016; Duchesne et al., 2013; Rokstad & Ugarelli, 2015; Tran, 2016;
- the availability of historical records of rehabilitated segments: Egger et al., 2013; Ouellet & Duchesne, 2018; Scheidegger, Hug, Rieckermann, & Maurer, 2011;
- the availability and quality of appropriate explanatory factors for model calibration: Ahmadi, Cherqui, De Massiac, & Le Gauffre, 2015; Mashford et al., 2011;
- the survival bias and issues linked to data censoring: Duchesne et al., 2013; Egger et al., 2013; Ouellet & Duchesne, 2018; Scheidegger & Maurer, 2012.

Several studies have shown that, despite the above mentioned sources of uncertainty, deterioration models are, to a certain degree, reliable tools to simulate the deterioration of the entire network (Duchesne et al., 2013; Hernández, Caradot, Sonnenberg, Rouault, & Torres, 2018; Ugarelli et al., 2013) and to identify segments in critical condition (Fuchs-Hanusch, Günther, Möderl, & Muschalla, 2015; Harvey & McBean, 2014; Rokstad & Ugarelli, 2015). It has also been shown that they can provide satisfying accuracy at the network level even in case of low data availability (Caradot et al., 2017; Duchesne et al., 2013; Tran, 2016). However, to the authors' knowledge, no study has investigated the influence of data quality on the reliability of modelling outcomes.

Deterioration models are trained or calibrated with sewer condition scores obtained from sewer visual inspection. Visual inspection and more specifically closed-circuit television (CCTV) inspection is the most used method to assess the condition of sewer segments (Knolmar & Szabo, 2003). The analysis of the image enables to identify the type and location of defects like offset joints, segment cracks, leaks, sediments, debris and root intrusions. The prevalence of CCTV compared to other existing techniques is explained by its low cost and the existence of national and European standards. The reliability of CCTV has been strongly questioned these last few years in the scientific literature (Caradot, Rouault, Clemens, & Cherqui, 2018a; Dirksen et al., 2013; Korving & Clemens, 2004; Roghani, Cherqui, Ahmadi, Le Gauffre, & Tabesh, 2019; Sousa et al., 2014a; van der Steen, Dirksen, & Clemens, 2014; van Riel, van Bueren, Langeveld, Herder, & Clemens, 2016).

According to these studies, condition assessment based on CCTV tends to underestimate the level of deterioration of segments. Condition assessment errors come from (Cherqui, Gutierrez-Silva, Ahmadi, Aubin, & Le Gauffre, 2017): the environment of the segment (e.g. obstacles which hinder accurate visualisation); the condition assessment procedure (e.g. coding system used, experience and subjectivity of the operator); the segment characteristics (e.g. diameter, material); and the defects characteristics (e.g. size, number, spatial distribution). Most utilities acknowledge the uncertainties in the procedure of sewer condition assessment, mainly due to the subjectivity of the coding operator. However, the importance of this uncertainty and its influence on the outcomes of deterioration modelling remain unknown. Our study aims at addressing these issues with the following objectives:

- quantify the uncertainties of the sewer condition assessment procedure;
- assess the influence of this uncertainty on the shape of the survival curves and on the predicted strategies of a deterioration model.

2. Material and method

The methodology that will be presented in the sequence, is based on the following three steps (Figure 1):

- Step 1: the determination of the uncertainty matrix using a set of repeated inspections of the same segments. The uncertainty matrix gives the probability to correctly estimate or misestimate the real condition of a segment using CCTV inspection.
- Step 2: the calibration of a statistical deterioration model and the propagation of the uncertainties in the survival curves.
- Step 3: the prediction of simple asset management strategies with and without considering uncertainties.

2.1. Step 1: Uncertainties in sewer condition assessment

Caradot et al. (2018a) proposed a methodology to assess uncertainties of sewer condition assessment based on the analysis of repeated inspections of the same segments. The aim is to determine the probability to underestimate, overestimate or accurately estimate the real condition of a segment using CCTV inspection. The methodology assumes that each inspected segment has a *real* structural condition which describes the rehabilitation needs. The *real* condition

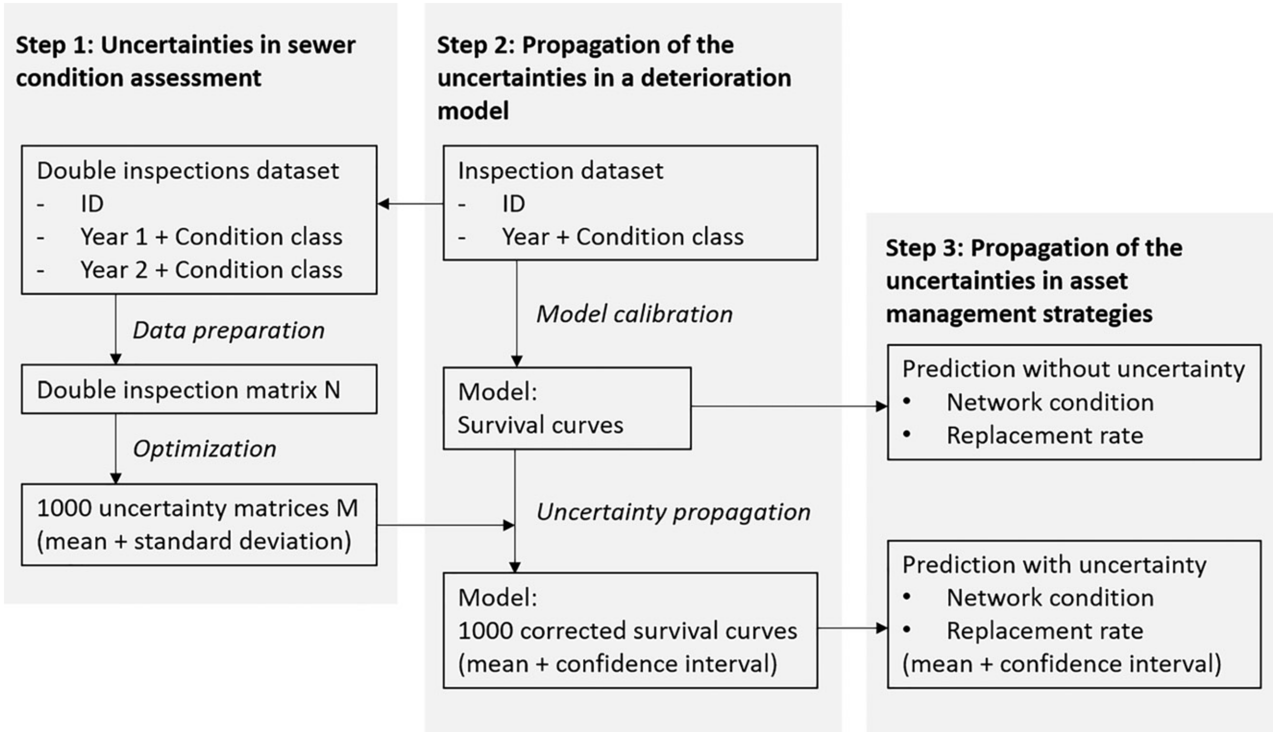

Figure 1. Presentation of the main steps of the methodology.

is defined as the sewer internal condition that would lead to the best rehabilitation (or no-rehabilitation) decision. The *real* condition of the segment is unfortunately unknown but can be estimated with an *inspected* condition, following the steps of CCTV visual inspection, sewer defect coding and sewer condition assessment. The *inspected* condition might estimate correctly the *real* condition but can also underestimate or overestimate it since uncertainties affect each step of the condition assessment procedure.

Uncertainties can be expressed in a matrix $M = P(\beta = i\alpha = j)_{i,j}$ which gives the conditional probability to be inspected in condition 'i' when a segment is really in condition 'j':

$$M = \begin{pmatrix} P(\beta = 1\alpha = 1) & P(\beta = 1\alpha = 2) & P(\beta = 1\alpha = 3) \\ P(\beta = 2\alpha = 1) & P(\beta = 2\alpha = 2) & P(\beta = 2\alpha = 3) \\ P(\beta = 3\alpha = 1) & P(\beta = 3\alpha = 2) & P(\beta = 3\alpha = 3) \end{pmatrix} \tag{1}$$

The term α indicates the real condition of a segment (which is unknown), while the term β indicates the inspected condition of a segment (which is known). The uncertainty matrix can be used to estimate the *inspected* condition distribution P of a network from the *real* condition distribution R:

$$P = MR \tag{2}$$

Similarly, the *real* condition distribution of a network can be estimated from an *inspected* condition distribution, providing that the matrix M is invertible, which would define R uniquely:

$$R = M^{-1}P \tag{3}$$

Supplementary material, Appendix 1 recalls the main steps of the optimisation methodology, which leads to the determination of the uncertainty matrix M. The optimisation is run 1000 times in order to deliver the mean and standard deviation of the uncertainty matrix M. The full approach has been published in a previous paper (Caradot et al., 2018a).

2.2. Step 2: Propagation of the uncertainties in the deterioration model

The obtained uncertainty matrix M can be used to propagate uncertainties in any survival model that predicts a probability class output (probability for a segment to be in a given condition class) from the segment's age and a set of numerical or categorical variables. The survival curves SC of a survival model give the probability to be in each condition at a given segment age T. For examples, with three condition classes:

$$\begin{aligned} P(T) &= (P_1(T),\ P_2(T),\ P_3(T)) \\ &= (SC_1(T),\ SC_2(T) - SC_1(T), 1 - SC_2(T)) \end{aligned} \tag{4}$$

During the calibration procedure, survival curves are estimated from a set of inspected segments. They aim at reproducing the deterioration behaviour observed in the inspection dataset, that is, the proportion of segments in each condition at a given age. After estimating the average uncertainty matrix, the survival curves can be corrected using Equation (3) as follows:

$$R(T) = M^{-1}\ P(T) \tag{5}$$

A confidence interval can be obtained from a Monte-Carlo simulation using the 1000 uncertainty matrices M obtained in the optimisation procedure. The confidence interval can be useful to propagate uncertainties in the prediction of the deterioration model. Monte-Carlo simulations allow simulating the impact of uncertainties on the strategic outcomes of the model.

It is worth noting that the uncertainties are propagated directly in the survival curves of the deterioration model: the *simulated proportion* of segments in each condition is corrected by the uncertainty matrix. Another approach would have consisted in propagating uncertainties in the condition data used as input for the model calibration. The uncertainty matrix would be applied to generate a random condition for each inspected segment. The corrected condition classes would then be used to calibrate the survival curves of the deterioration model. In this case, the *inspected proportion* of segments in each condition is corrected by the uncertainty matrix. The two approaches lead to similar survival curves since the inspected and simulated proportions of segments in each condition are similar (the deviations between the inspected and simulated proportions is close to 0 for a good calibrated model (Caradot et al., 2017)). The first approach presented above has been preferred for its computational simplicity: the Monte-Carlo simulation is used to correct the survival curves instead of correcting the condition data used as input for the model calibration.

2.3. Step 3: Propagation of the uncertainties in asset management strategies

First, the corrected survival curves are used to simulate the future evolution of the condition distribution of 1000 random segments for a fictive do-nothing strategy without any rehabilitation action. Over a given simulation period [T_{start}; T_{end}], the model calculates, for each year T, the condition distribution, that is, the proportion of segments in each condition:

$$C(T) = (C_1(T),\ C_2(T),\ C_3(T)) \tag{6}$$

Then, the survival curves are used to simulate the necessary replacement rate to maintain the condition of the whole network over time (constant proportion of segments in poor condition). The replacement rate is calculated as the percentage of segments that shifted from the intermediate to the poor condition between the start year and a given year of the simulation, divided by the number of elapsed years. It provides the average yearly replacement rate to avoid the deterioration of the network:

$$replacement\ rate\ (T) = \frac{C_3(T) - C_3(T_{start})}{T - T_{start}} \tag{7}$$

2.4. Application on the sewer network of the city of Berlin

2.4.1. Description of the data

The study has been performed using the extensive GIS and CCTV databases of the city of Berlin in Germany (3.7 million inhabitants). The sewer network is composed of 235,988 segments (9710 km) registered in the GIS database. Most segments are sanitary sewers (45%) whereas 35% are stormwater sewers and 20% are combined sewers. Clay and concrete are the two dominating materials with respective proportions of 54% and 25%. The Berliner Wasserbetriebe conducts extensive CCTV inspection programmes since the end of the 1980s. Sewer defects observed during inspections are systematically coded in a local coding system comparable to the German guideline ATV M 143-2 (1999).

Sewer structural condition is evaluated using an internal company classification system with six grades similar to the German guideline DWA-M 149-3 (2011). The algorithm considers the most severe defect as well as the length and density of the defects. It includes a wide range of structural and operational defects such as fissure, collapse, surface damage, displaced joint, attached deposit, infiltration, root intrusion, etc. The six grades have been aggregated into three grades indicating the emergency of rehabilitation (i.e. 1. good condition; 2. intermediate condition and 3. poor condition with urgent rehabilitation need). After data preparation (consistency check, filtering and clean up), 124,450 inspections with a length of 5222 km for 107,788 different segments were available for the study.

2.4.2. Calibration of a deterioration model

Figure 2 shows the condition distribution of the dominating clay and concrete pipes (99,058 inspections). Pipes with other materials such as reinforced concrete, asbestos cement, brick or plastic have not been considered in the analysis.

The condition is correlated with the segment's age; old segments are in worse condition than new segments. However, the condition of very old and depreciated segments (>90 years old) seems to improve slightly. This phenomenon is known as survival selection bias (Egger et al., 2013; Ouellet & Duchesne, 2018). Inspection data have a tendency to be biased as the observations are carried out in a restricted time window (for this study from 2001 to 2017). Most old or deteriorated segments have already been replaced, thus are not fully represented in the sample of inspection data. In order to remove (or at least reduce) the influence of the survival bias in model calibration, old segments (age > 70 years old for concrete pipes; age > 90 years old for clay pipes) have been removed from the dataset.

The model GompitZ (Le Gat, 2008) has been used to calibrate survival curves for one unique cohort composed of concrete and clay segments and using the segment age as unique variable. Survival curves have the mathematical form of a Gompertz distribution (Equation (8)). They are calibrated with a regression procedure using the maximum likelihood estimation:

$$SC_k(t) = e^{\left(-e^{\alpha + te^{\beta}}\right)} \tag{8}$$

with SC_k the survival function for the condition k; t the age of the segment; α and β the calibrated parameters of the Gompertz distribution.

This survival model has been selected for its conceptual and computational simplicity. The main drawback of survival models is that they require an extensive dataset to create cohorts with sufficient inspected sewers in each condition state for the calibration of the transition functions (Kley &

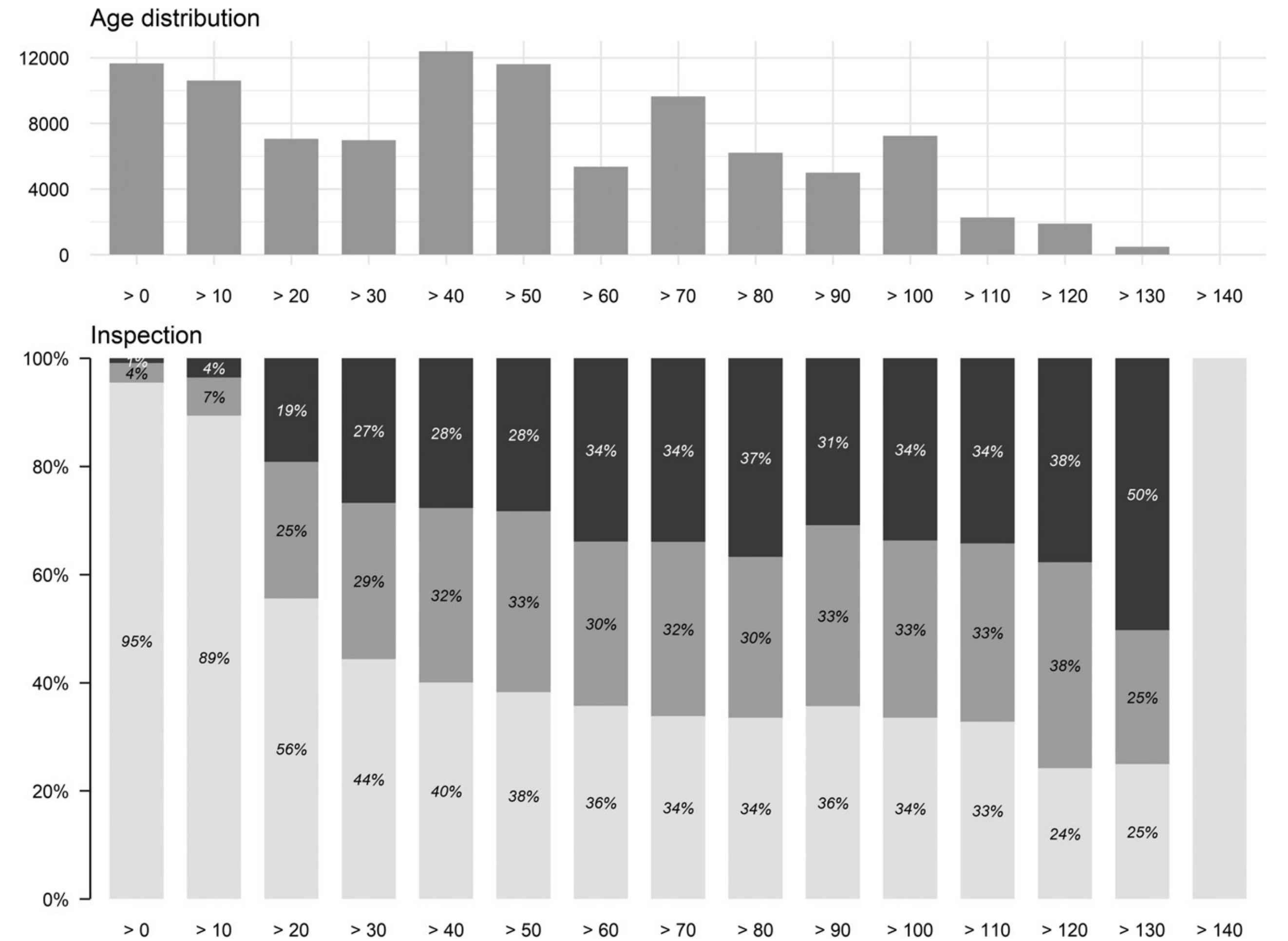

Figure 2. Condition distribution VS segment age for the inspected concrete and clay segments in Berlin. The grey scale represents the three condition classes, dark grey being the proportion of segments in the worst condition (condition 3). The *y*-axis indicates the proportion of segments in each condition (in number of segments). The *x*-axis indicates age groups of 10 years.

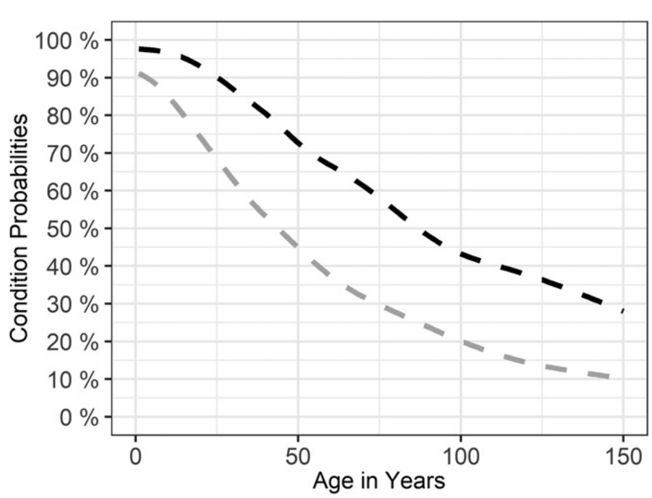

Figure 3. Calibrated survival curves for concrete and clay segments. The light grey curve shows transition from good condition: (1) to intermediate condition (2). The dark grey curve shows transition from intermediate condition (2) to poor condition (3). The *y*-axis gives the probability to be in each condition at a given segment age (*x*-axis).

Caradot, 2013). For this study, this issue has been addressed by grouping segments into one unique cohort composed of concrete and clay segments (99,058 inspections).

The performance of the model has been assessed by analysing the deviation between the predicted and inspected condition distributions (Caradot et al., 2018b). At the network level, the deviations between the inspected and simulated proportions of segments in each condition are very low (<1%). By grouping segments into age periods of 25 years (0–25 y; 26–50 y; 51–75 y), the deviations between the inspected and simulated proportions of segments in each condition are below 10%. The performance of the model could be improved by considering additional covariates such as the material, the depth, the shape and the type of effluent (Caradot et al., 2018b). For example, the model could be calibrated separately for concrete and clay pipes to account for their different deterioration patterns (Davies et al., 2001). However, for the purpose of this study, the simplicity of the model is more important than the performance since the aim is to understand the sensitivity of the model to input data uncertainties.

Figure 3 depicts the calibrated survival curves for the three condition classes. The curves reproduce the deterioration behaviour of concrete and clay segments observed in Figure 2. The influence of the survival bias has been estimated by calibrating the model with all data, that is, without removing old pipes. As expected, the prediction is more pessimistic by removing old pipes from the databases (e.g. +10% pipes in poor condition at 100 years; results not shown here).

3. Results and discussion

3.1. Step 1: Uncertainties in sewer condition assessment

The methodology described in Caradot et al. (2018a) has been applied using the inspection data of Berlin. Supplementary material, Appendix 1 presents in detail the results of the methodology. The main uncertainty matrix M obtained from the optimisation procedure is:

$$mean\ (M) = \begin{pmatrix} 85.2 & 15.9 & 6.1 \\ 10.6 & 67.3 & 12.5 \\ 4.2 & 16.8 & 81.4 \end{pmatrix} \quad (9)$$

Main outcomes can be highlighted as follows:

- For segments in good condition (1), the probability of assessing correctly the condition is 85.2%. On the other hand, the probability to underestimate the condition is 14.8%: False Positive, that is, the inspected condition is worse than the real condition (e.g. defects have been considered more serious than they really are).
- For segments in poor condition (3), the probability of assessing correctly the condition is 81.4%. On the other hand, the probability to overestimate the condition is 18.6%: False Negative, that is, the inspected condition is better than the real condition (e.g. defects have been missed by the operator).
- The probability to inspect correctly a segment in intermediate condition (2) is lower because the assessment can lead to both False Positive and False Negative. The intermediate condition is more ambiguous to assess as the segment neither is in perfect condition, nor already failed. Another reason can be the narrow range of defect characterisation and quantification that leads to intermediate condition (2).

3.2. Step 2: Propagation of the uncertainties in a deterioration model

The uncertainty matrix can be used to propagate uncertainties in the survival model and to assess their influence on the prediction of asset management strategies. Equation (5) is applied to correct the survival curves presented in Figure 3. For each age T, the corrected survival curves are obtained by multiplying the proportions of each condition from the survival curves by the uncertainty matrix. A total of 1000 corrected survival curves are generated using the 1000 uncertainty matrices obtained during the optimisation procedure. From the 1000 corrected survival curves, the mean corrected survival curves and the boundaries of the 90% confidence interval are calculated.

The confidence interval quantifies the uncertainty of the prediction, for example, at 100 years, the proportion of segments in poor condition is 65% ± 12%. The mean corrected

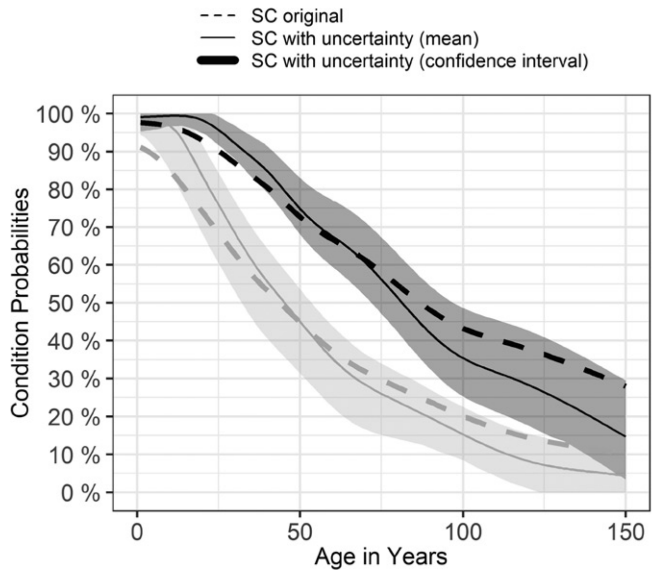

Figure 4. Original and corrected survival curves. Light grey curves show transition from good condition (1) to intermediate condition (2). Dark grey curves show transition from intermediate condition (2) to poor condition (3). The y-axis gives the probability to be in each condition at a given segment age (x-axis).

survival curves do not overlap with the original survival curves. It indicates that the propagation of uncertainties corrects a systematic error: the average prediction considering uncertainties (solid lines in Figure 4) is not equal to the prediction without considering uncertainties (dashed lines in Figure 4). This bias is related to the different probabilities of False Positive and False Negative. As discussed in the previous section, the most probable errors are False Positive for segments in good condition and False Negative for segments in poor condition. Most of the young segments (<30 years) are in good condition and are thus more prone to False Positive than False Negative.

There is a higher probability to be too pessimistic, thus, the corrected survival curve is more optimistic than the original survival curve.

In contrast, most of the old segments (>75 years) are in poor condition and are thus more prone to False Negative than False Positive. It is also worth mentioning that the slopes of the original and corrected survival curves are not identical. The slope of the corrected survival curves is higher indicating that the systematic error increases with age. The correction leads to a faster network deterioration. There is a higher probability to be too optimistic, so the corrected survival curve is more pessimistic than the original survival curve.

3.3. Step 3: Propagation of the uncertainties in asset management strategies

In the previous section, uncertainties from sewer condition assessment have been propagated in the calibrated survival curves of a deterioration model. Since models are used to simulate asset management strategies, it is of interest to assess the sensitivity of the predicted strategies to these uncertainties.

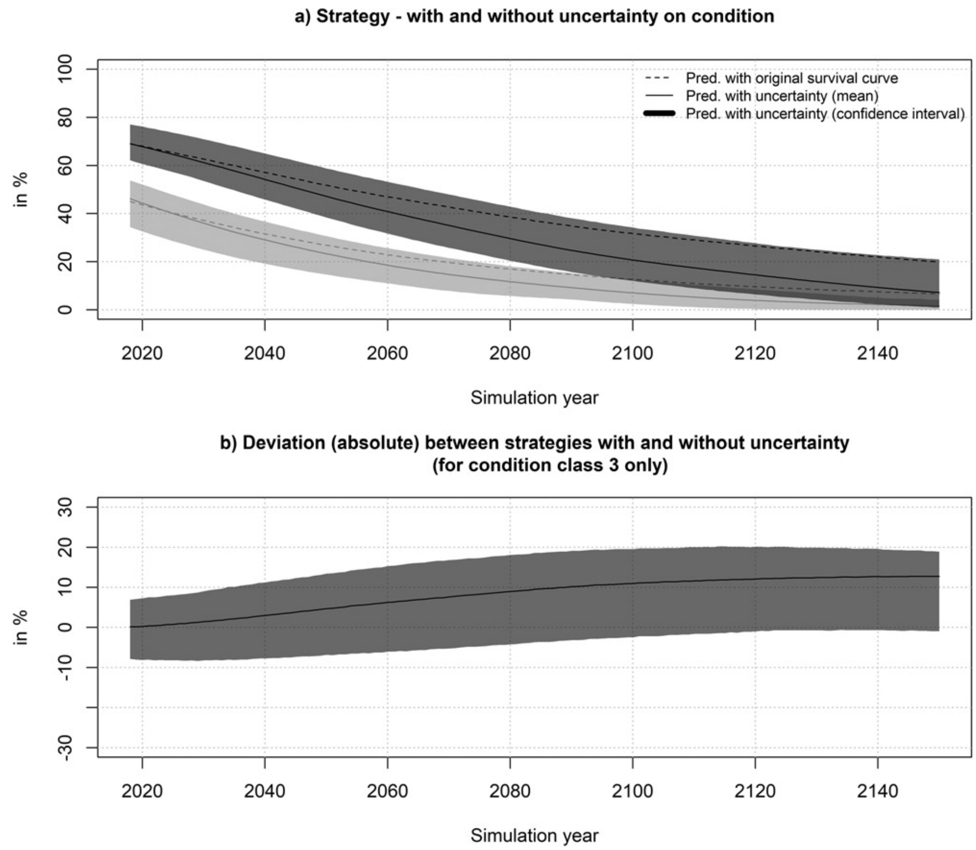

Figure 5. Impact of uncertainties on the prediction of a deterioration model. Simulation of a do nothing strategy for 1000 random segments in Berlin. Light grey curves show the percentage of segments in good condition (1). Dark grey curves show the percentage of segments in good (1) and intermediate (2) conditions. (a) The *y*-axis shows the proportion of segments in each condition, with and without considering uncertainties, at a given simulation year (*x*-axis). (b) The *y*-axis shows the deviation between the simulated proportions of segments in bad condition, with and without considering uncertainties, at a given simulation year (*x*-axis).

3.3.1. Impact of uncertainties on the predicted condition of the network

First, the survival curves have been used to simulate the future evolution of the condition distribution of 1000 random segments for a fictive do-nothing strategy, that is, without any rehabilitation action. The experiment has been run on 1000 segments selected randomly among the entire network to reduce the computation time of the Monte Carlo simulation. Figure 5a shows the evolution of condition distribution using the original survival curves and the corrected survival curves (with mean and 90% confidence interval). Figure 5b presents the absolute deviation (in %) between the proportions of segments in poor condition (3) obtained with the original and corrected survival curves. The long-time horizon (>100 years) is not realistic for planning strategies but interesting to understand the sensitivity of the models.

In 2060, according to the original survival curves, the proportion of segments in poor condition would be 53% (Figure 5a). By considering uncertainties, the proportion rises to 59% ± 11% (Figure 5a). The following outcomes can be highlighted:

- The impact of the uncertainties is not negligible. Even at the start simulation year, the proportion of segments in poor condition can be estimated correctly within a range of ± 8% (Figure 5b).
- The prediction uncertainty increases with the simulation year. In particular, the systematic error (bias between the average prediction considering uncertainties and the prediction without considering uncertainties) increases with the simulation year. In 2060, the prediction uncertainty is ±11% with a systematic uncertainty of +6%. The systematic uncertainty would reach +10% only after 2090 (Figure 5b). At this time horizon, other uncertainties (e.g. urban development; new pipes material) are likely to have much more influence on the outcomes than the uncertainty of the condition assessment, making predictions highly unrealistic.

3.3.2. Impact of uncertainties on the replacement rate

In the second experiment, the survival curves have been used to simulate the necessary replacement rate to maintain the network with a constant proportion of segments in poor condition over time, for the same subset of 1000 random segments. This proportion can be read at the start simulation year in Figure 5a. Figure 6 displays the replacement rates obtained with the original and corrected survival curves. Using the original survival curve, the necessary replacement rate ranges between 0.5% and 0.6%. Considering uncertainties, the replacement rate is higher. Until 2050, the average replacement rate obtained by the original survival curve is 0.54%, and the corrected

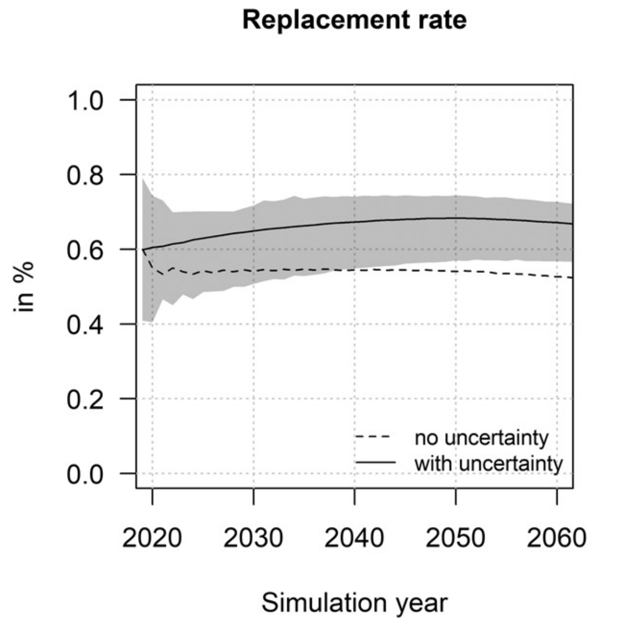

Figure 6. Impact of uncertainties on the required replacement rate to maintain the network with a constant proportion of segments in poor condition over time, for 1000 random segments. The *y*-axis shows the simulated replacement rate with and without considering uncertainties, at a given simulation year (*x*-axis).

replacement rate ranges between 0.57% and 0.75%. This result can be understood from the slopes of the survival curves. The slope of the corrected survival curves is higher than the slope of the original survival curves indicating a faster network deterioration. The consideration of uncertainties leads to a higher and more accurate replacement rate.

Note that the calculated replacement rate is not the required replacement rate to avoid the global deterioration of the network (i.e. constant proportion of segments in each condition) but only to maintain a stable proportion of segments in condition class 3 (poor condition) over the next 30 years. This replacement rate would be too low to avoid the global deterioration of the network since the proportion of segments in intermediate condition would increase meanwhile the proportion of segments in good condition would decrease.

4. Conclusions

This paper analyses the influence of sewer condition uncertainties on the prediction of deterioration models. Uncertainties of condition assessment are a well-known issue for sewer operators who generally acknowledge the high subjectivity of the condition assessment procedure. First, a methodology has been applied to quantify uncertainties in sewer condition assessment from the analysis of a set of repeated inspections. The repeated inspections have been used to determine the uncertainty matrix, which quantifies the probability to inspect a segment correctly and to overestimate or underestimate its condition. Then, a method has been proposed to propagate uncertainties in the survival curves and predictions of a deterioration model. The deterioration model has been used to simulate simple long-term strategies and evaluate the impact of condition uncertainties over the model prediction period.

The method has been demonstrated using the inspection dataset of the city of Berlin, Germany, where 13,753 segments have been inspected at least twice. The following outcomes can be highlighted.

- The probability to assess the correct condition of a segment in good condition is 85%; the probability to assess the correct condition of a segment in poor condition is 81%. The probability to assess the correct condition of a segment in the intermediate condition is lower and close to 67%.
- The uncertainties in sewer condition assessment are not only due to the inspection procedure. The analysis of deviations in repeated inspections by the water utility highlights further sources of uncertainties such as undocumented rehabilitation (i.e. the rehabilitation of segment has not been documented in the database) or inspections done with a specific purpose, e.g. to identify house connections. The reduction of uncertainties could start by improving data management procedures in order to be able to filter improper inspections for calibrating sewer deterioration models.
- The propagation of uncertainties in the survival curves produces a confidence interval around the original survival curves. At 100 years, the uncertainty for the proportion of segments in poor condition is ±12%.
- The analysis of this confidence interval highlights the presence of a systematic error: the mean corrected survival curves do not overlap with the original survival curves. This bias is related to the different probabilities of False Positive and False Negative.
- The impact of the uncertainties on the prediction of a deterioration model is not negligible. The systematic uncertainty increases with the simulation year. The analysis also shows that the required replacement rate to maintain a constant proportion of segments in poor condition is underestimated if the uncertainties are not included in the analysis.

Even influenced by uncertainties, deterioration models remain a powerful tool to assess the impact of future rehabilitation scenarios at network scale. However, the high uncertainties in deterioration modelling must be communicated to avoid the wrong interpretations of modelling outcomes and wrong management decisions. It is recommended to focus on the mitigation of uncertainty sources and the visualisation of the remaining uncertainties in asset management tools to facilitate decision making in a highly uncertain context.

In particular, the survival bias seems to be a critical uncertainty source for the future development of deterioration models (Ouellet & Duchesne, 2018). Current models are expected to overestimate the real condition of the network because the observed segments used for model calibration are only those that ‘survived’ until the date of inspection, that is, segments that were not replaced before they reach their current degradation state (Le Gat, 2008). Several studies already highlighted the existence of this bias using synthetic datasets (Ouellet & Duchesne, 2018) or by combining deterioration models with theoretical rehabilitation models (Egger et al., 2013). Further work will be needed to quantify this bias using real datasets by considering the data from already replaced segments in model calibration. Further investigations are also needed to propose practical methodologies to correct locally the survival bias in order to avoid the presence of systematic errors in long-term predictions.

Given the considerable annual investments for sewer rehabilitation (e.g. >80 million euros in Berlin), additional expenses on sewer inspection and data management for the reduction of model uncertainties might be beneficial to optimise the strategic planning of investments on the network. Further studies might investigate in detail the marginal benefits of reducing modelling uncertainties in order to determine the appropriate level of expenses for sewer inspection and data management.

Disclosure statement

No potential conflict of interest was reported by the authors.

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