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Defect Evolution in Sewer Pipes: Enhancing Deterioration Models

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Abstract

Deterioration models for sewer pipes often rely only on aggregated pipe-level data (pipe condition), without considering individual defects and their evolution. Is-it worth considering individual defects to improve deterioration models? A preliminary answer is to know if it is possible to model the evolution of individual defects. This study presents a methodology for analysing defect transitions in multi-inspected sewer pipes to gain insights into the aging and deterioration processes at the defect level. Using inspection data provided by Berliner Wasserbetriebe, covering 242,920 pipes and nearly 1.9 million observations, incl. defects encoded according to EN 13508-2, defect transitions were analysed across 24,734 inspection pairs. Defects between inspection pairs for each pipe and position are mapped, creating a transition matrix and knowledge graph to highlight defect inter-dependencies. The results reveal plausible transitions, such as gradual surface degradation from increased roughness to missing pipe wall parts, with varying durations, but also transitions that may reflect inspection uncertainties. Future work will incorporate defect severity classes and explore how these insights can enhance machine learning models through feature engineering or domain-informed approaches.

Highlights

- Analysis of defect evolution and transition from multiple inspections of the same pipe
- Knowledge graph to represent transition probabilities and average time for defect transitions
- Insights on defect-level may be used for machine learning-based condition prediction

Introduction

Deterioration or condition prediction models are crucial for estimating the sewer pipe condition when comprehensive or up-to-date data is unavailable. Current approaches to condition prediction models are predominantly data-driven, leveraging statistical and machine learning methods (Tscheikner-Gratl et al., 2019). While these models rely on general pipe features – such as age, material, or length – to estimate the overall pipe condition (Malek Mohammadi et al., 2020), the actual pipe condition is based

on observed and classified (e.g., by EN 13508-2) defects, their characterizations, and the aggregation rules that translate the presence of individual defects into a pipe condition class. This aggregation groups diverse defect types, some of which may actively deteriorate while others remain stable (Rokstad and Ugarelli, 2016). As a result, these models predict a condition class that reflects mixed causes, some unrelated to actual deterioration, complicating accurate predictions. Yet, data-driven condition prediction models lack access to detailed defect information, relying instead on correlations between the aggregated condition and broader pipe and environmental factors (like pipe age, material etc). Adding information about previous defect types, their aging status, and progression could enhance model accuracy. Only few studies, such as Jimenez-Roa (2025) and Elmasry et al. (2017) examined failure mechanisms based on individual defects. Moreover, supplementing benchmarked condition prediction models, such as in Caradot et al. (2018) with additional knowledge about the presence of defect with certain aging characteristics was not found in existing publications.
The motivation for this study is driven by the hypothesis, that different defect types can have various deterioration speeds and that the occurrence of fast aging defects will lead to faster pipe condition degradation. As these processes are hidden by traditional condition prediction modelling on pipe level, this study aims to investigate deterioration processes on defect level in order to bring these insights back into condition prediction models on pipe level. The research presented in this abstract explores whether examining defect evolution and transitions provides deeper insights into deterioration processes to be used for deterioration modelling.

Methodology

Analysis of multiple sewer pipe inspections

Data from multiple inspections, at least one year apart, were paired. For pipes with more than two inspections, all possible combinations of inspection pairs were included in the dataset. Only pairs without repairs, renovations, or renewals in between the two inspections were considered. Due to unreported repairs, pipes showing condition improvement were excluded to mainly account for degradation processes. Defects were assessed at identical positions in the same pipes across these pairs.

Selection and processing of defect data

Defects (listed in Table 1) were selected based on two criteria: (1) sufficient occurrences during paired inspections and (2) importance for the condition of the pipe or potential for leading to other defects over time. Additionally, the first characterization of each defect was considered if available in the dataset in order to distinguish the defects as precisely as possible (for example BAF is a surface damage: BAF A corresponds to increased roughness, and BAF I corresponds to missing wall). Hence, defect codes form a three- to four-letter code according to EN 13508-2. Similar defects and characterizations were grouped to account for assessment uncertainties (e.g., BAF A+B, BAF C+D, BAO+BAF I, see Table 1 for their signification). For each inspection pair, defects from the first and second inspection were mapped by position, and all possible combinations of first- and second-inspected defects were analysed as defect transitions. Defect transitions with the same origin and

		Second Inspection		
		Defect 1	Defect 2	Sum of rows (SoR)
First Inspection	Defect 1	t1,1	t1,2	SoR(1) = t1,1 + t1,2
	Defect 2	t2,1	t2,2	SoR(2) = t2,1 + t2,2

Figure 1. Conceptual transition matrix representing all defect transitions for inspection pairs with t being the number of transitions/links between a firstly and secondly inspected defect

destination were aggregated, and the average time difference between inspection pairs was calculated. Figure 1 shows a conceptual transition matrix, where each cell represents the number of first-inspected defects leading to second-inspected defects. The sum of rows (SoR) shows transitions originating from a specific defect, while the sum of columns (SoC) shows transitions leading to a specific defect.

Normalization of defect transitions and graph building

Normalization of defect transitions is essential due to dataset imbalance. Some defects (e.g., collapse/BAC C) occur less frequently than others (e.g., fissures/BAB C), but frequency doesn't necessarily correlate with transition likelihood. Therefore, normalization is performed by dividing each transition from defect 1 to 2 by the sum of the total transitions originating from defect 1 and the total transitions to defect 2. For example, $p1{,}2 = \frac{t1{,}2}{SoR(1)+SoC(2)}$. The resulting transition probabilities show how often transitions from defect 1 to defect 2 occur relative to all possible transitions involving these defects. A knowledge graph consisting of nodes (defects) and links (transitions) is then created to represent the probability of defect transitions and the average time to subsequent defects.

Case study

The pre-processed dataset from Berliner Wasserbetriebe contains in total 242,920 inspected pipes, including multiple inspections of the same pipes. The sewer pipes, spanning ca. 9,175 km, range between 5 and 120 years of age, mainly consist of vitrified clay (ca. 60%) and concrete (ca. 25%) and represent 45% wastewater, 36% stormwater and 19% mixed pipes. The dataset of defects that are observed during the inspections and encoded according to EN 13508-2 includes nearly 1.5 million defects (functional inventories, like BCD or BCE / start or finish node were excluded). Pairing all combinations of multiple inspections yielded 24,734 inspection pairs. Filtering for selected defects (Table 1) with characterizations resulted in 32,147 defect combination pairs for further analysis. Table 1 summarizes the selected defect categories, their characterizations, and frequencies across the inspection pairs. Surface damage (BAF) defects dominate, accounting for over 50% of the dataset, while more severe defects like collapse (BAC C) occur far less frequently.

Table 1. Selected defects for further analysis

Codes	Defect category	Characterization	No. of defects in inspection pairs	Perc. of defects [%]
BAA A	Deformation	vertical deformation	1,200	1.9
BAB C	Fissure	open fracture	7,251	11.3
BAC A	Break/collapse	displaced wall pieces	458	0.7
BAC B	Break/collapse	missing wall pieces	9,674	15.0
BAC C	Break/collapse	collapse	319	0.5
BAF A+B	Surface damage	increased roughness + spalling	17,655	27.5
BAF C+D	Surface damage	visible/projecting aggregate	16,021	24.9
BAF E	Surface damage	missing aggregate	4,001	6.2
BAO+BAF I	Surface damage	missing wall / soil visible	7,715	12.0

Results and discussion

The relationships between defects to other defects through inspection pairs can be seen as graph-structured data that can be represented in a knowledge graph. Figure 2 illustrates normalized transition probabilities between aggregated defect pairs based on inspection data. Applying cut-offs of ≥ 5% transition probability and ≥ 5 years between inspections excludes less significant transitions from the adjacency matrix. For better clarity, the self-loops of each defect are omitted in this knowledge graph. A plausible progression is observed in the surface degradation category (BAF A+B → BAF C+D → BAF E → BAO/BAF I). An interesting insight is the average time of transition with BAF A+B to BAF C+D occurring after 11 years on average, while subsequent stages (BAF C+D → BAF E or

BAO+BAF I) progress faster, taking approximately 7 years. Another plausible transition is BAC A → BAA A, whereas the unlikely transition BAC C → BAC A might reflect inspection inaccuracies, such as overestimating a collapse during the first inspection and later reclassifying it as displaced wall pieces. The same applies to the link from BAB C to BAF A+B. Uncertainties and errors in CCTV inspections, as well as defect detection and classification, must be considered when interpreting these analyses. Additionally, missing repair data showed pipes that improved over time, which haven been excluded from this analysis. Therefore, the graph should not be viewed as a perfect representation of the phenomena. Moreover, it is important to note that defect transitions do not always indicate direct causality. Defects observed in repeated inspections might arise independently due to shared conditions, such as pipe structure or environmental factors, rather than degradation caused by earlier defects.

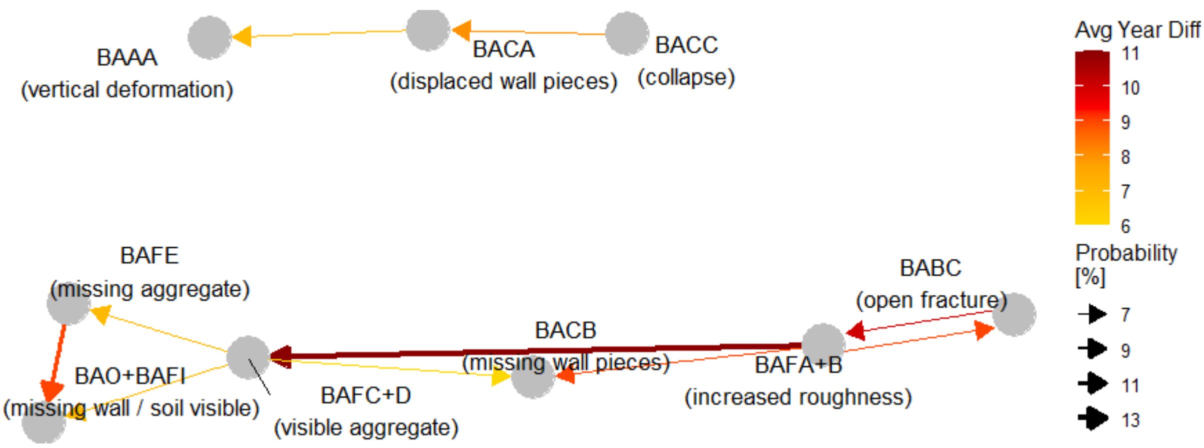

Figure 2. Knowledge graph of defect transitions, with link thickness indicating transition probability and color scale (yellow: 6 years, dark red: 11 years) representing average transition time; created in R using the packages: igraph, ggraph.

Conclusions and future work

This study introduces an innovative approach to analysing sewer pipes through multiple inspections, focusing on defect transitions to deliver detailed insights into the aging and degradation process at the defect level. By analysing the probability of defect transitions over time, the methodology provides a valuable framework for understanding defect evolution.

Future work will incorporate defect severity classes to explore defect transitions in greater detail and assess the influence of pipe characteristics and environmental factors for predictive modelling. Additionally, these insights may support feature engineering in machine learning and could further contribute to developing educated machines that integrate domain knowledge to data-driven approaches. For example, defect evolution insights could inform aging scores specific to previously inspected defects, guiding machine learning models with predefined transition probabilities as supplementary domain knowledge.

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