

Enhanced Sewer Condition Prediction Using Prior Defect Observations

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Highlights

- Defect-based features from consecutive inspections improve model performance.
- Enhanced prediction of pipes newly deteriorated since the last inspection.

Introduction

Many utilities have already inspected large parts of their sewer networks. From these past inspections, they already know which pipes were in severe condition at that time. Their current challenge is different: They want to identify the pipes that worsened to a severe condition since the last inspection – pipes that were previously in good or average condition but may now require urgent rehabilitation. Condition prediction models are widely used to support this task. Most existing models are data-driven and estimate pipe condition using general pipe features such as age, material, or length (Malek Mohammadi et al., 2020). However, actual structural condition is derived from observed and classified (e.g., by EN 13508-2) defects and how these defects develop over time. Because current models do not explicitly include defect information from previous inspections, they neglect the actual drivers of deterioration and focus instead on correlating variables like age or material. This study addresses these issues by focusing on two key research questions: (1) Can deterioration models be improved by adding previously observed defects as input variables? (2) How well can such models identify pipes that newly fall into severe condition class since the last inspection? The overall objective is to increase the practical value of condition prediction for utilities by improved model performance and better identifying pipes whose condition has worsened since the last inspection.

Methods

A Random Forest model (Caradot et al., 2018) is applied to predict four structural condition classes (*good*, *medium*, *poor*, *very_poor*), using CCTV inspection data. Unlike previous modelling approaches, this model is trained on consecutively inspected pipes, enabling the use of defect-based predictors from the first inspection and the condition of the second inspection as the target. On this dataset, three model scenarios are tested:

- 1. Baseline Model (Pipe Attributes Only):** Uses standard attributes (age, length, material, etc.) according to (Caradot et al., 2018) and applies to both previously and not previously inspected pipes.
- 2. Defect-Enhanced Model (With Prior Defect Data):** Uses defect information from the earlier inspection to improve prediction of the second inspection condition. Defect-based features include: number of aging-relevant defects, main code of the most severe defect, defects with high potential to progress and age at previous inspection, derived from Guericke et al. (2025).
- 3. Defect-Enhanced Model + Upsampling:** Builds on Model 2 and duplicating all pipes for which the condition worsened from better class into more severe condition (see bolt values in Figure 1) in the training set, focussing the model on detecting these pipes of worsening condition.

Performance evaluation

Model performance is evaluated using precision (correct *very_poor* predictions among all *very_poor* predictions) and recall (share of actual pipes in condition *very_poor* correctly detected).

To assess the usefulness of the three models for utilities, a second evaluation is carried out on a filtered subset: Only pipes that deteriorated into *very_poor* condition after previously being in better condition are considered (see Figure 1: values in green box). Precision and recall are then calculated for this subset to measure how well the model detects pipes that are new to the condition *very_poor*.

Results and Discussion

All scenarios were tested on the same dataset with a total number of 26,913 pipes that have been inspected twice. Pipes that showed improved condition in the second inspection indicate lacking information about repair and were hence excluded. The transition matrix in Figure 1 confirms that most pipes remain stable between inspections (see diagonal), while a smaller subset deteriorates (see bolt values), providing the basis for the degradation-based upsampling of model scenario 3. The three scenarios explained in the methods section are simulated, using a 75/25% or 79/21% (upsampled model scenario 3) train-test split and separate optimal hyperparameter sets were applied with $mtry = 7/3$, $nodesize = 60/140$, $ntrees = 100$ for model scenario 1 and 2/3 respectively.

		1. inspection condition			
		<i>good</i>	<i>medium</i>	<i>poor</i>	<i>very_poor</i>
2. inspection condition	<i>good</i>	5428	0	0	0
	<i>medium</i>	3283	10090	0	0
	<i>poor</i>	454	2087	1176	0
	<i>very_poor</i>	214	1033	949	2299

Figure 1. Matrix of consecutively inspected pipes with condition of first inspection in columns and condition of second inspection in rows; with pipes new to condition “very_poor” in green, pipes already known in condition “very_poor” in red.

Table 1 shows a performance increase for the defect-enhanced model compared to the baseline model for both precision and recall. Thus, model scenario 2 both missed fewer severely degraded pipes and generated fewer false positives. Upsampling (model scenario 3) further increased the detection of previously unknown *very_poor* pipes, yielding the highest recall (58%), meaning over half of pipes that recently deteriorated were correctly identified. These approaches, however, require pipes with at least two inspections, using the first for deriving the defect features and the second as condition targets for model calibration. Once trained, the model can be applied to any pipe with at least one inspection.

Table 1. Modelling results for predicting pipes in condition *very_poor* generally, using recall and precision as well as specifically for pipes new to the condition *very_poor*, which have been in another condition class in the previous inspection

Scenario	All pipes in condition “very_poor”		Only pipes new to condition “very_poor”	
	Precision	Recall	Precision	Recall
1. Baseline Model	24 %	49 %	33 %	44 %
2. Defect-Enhanced Model	41 %	64 %	51 %	55 %
3. Defect-Enhanced Model + Upsampling	39 %	67 %	50 %	58 %

Conclusions and Outlook

This study shows that adding defect information improves deterioration modelling, increasing precision and recall for *very_poor* pipes by roughly 15–17 % compared to the baseline. It also demonstrates that these models more effectively identify pipes newly falling into *very_poor* condition since the last inspection, improving both precision and recall by about 12–17 %. These improvements enhance the practical value of condition prediction for utilities by better flagging emerging pipes in severe condition. Future work will test the calibrated model at Berlin utility to assess its practical value.

References

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