Cause and effect oriented sewer degradation evaluation to support scheduled inspection planning
D. Fuchs-Hanusch, M. Günther, M. Möderl and D. Muschalla

ABSTRACT
Managing the subsurface urban infrastructure, while facing limited budgets, is one of the main challenges wastewater utilities currently face. In this context targeted planning of inspection and maintenance measures plays a crucial role. This paper introduces a cause and effect oriented sewer degradation evaluation approach to support decisions on inspection frequencies and priorities. Therefore, the application of logistic regression models, to predict the probability of failure categories as an alternative to the prediction of sewer condition classes, was introduced. We assume that analysing the negative effects resulting from different failure categories in extension to a condition class-based planning approach offers new possibilities for targeted inspection planning. In addition, a cross validation process was described to allow for a more accurate prediction of sewer degradation. The described approach was applied to an Austrian sewer system. The results show that the failure category-based regression models perform better than the conventional condition class-oriented models. The results of the failure category predictions are presented with respect to negative effects the failure may have on the hydraulic performance of the system. Finally, suggestions are given for how this performance-oriented sewer section evaluation can support scheduled inspection planning.

Key words | CCTV data, logistic regression, probabilistic failure models, selective inspection strategy, sewer condition

INTRODUCTION
In the last century, substantial investments were made in the construction of sewerage systems. Maintaining the function of these infrastructures is a central task for wastewater utilities nowadays. Structural degradation of sewers can lead to a performance reduction of the system and in the worst case to a loss of functionality. Therefore, identifying the causes and effects of structural degradation is of major interest in sewer maintenance planning.

To identify the influences on structural degradation, several statistical models have been applied in the past. Davies et al. (2001), Ariaratnam et al. (2001) or Ana & Bauwens (2010) described the use of logistic regression models. In terms of the advantage of logistic models, Ana & Bauwens (2010) highlighted that they give insight into the deterioration process by identifying the most important variables affecting the process. Other statistical models like cohort-survival analyses (Baur & Herz 2002) or Markov chain-based models (Wirahadikusumah et al. 2001; Baik et al. 2006; Le Gat 2008) mainly focus on group-based predictions with the aim of deriving transition probabilities between condition classes. Contrary to the task of renewal planning, where transition-based models are essential to derive long-term strategies, for inspection and re-inspection planning, regression models are also suitable.

Many condition prediction methods are dedicated to predicting condition classes of sewer sections as a whole (Baur & Herz 2002; Baik et al. 2006; Le Gat 2008; Kleidorfer et al. 2013). For a performance-oriented approach, we assume that the prediction of specific sewer conditions, like fractures, collapse, deformation etc. is of special interest, as the resulting sewer failure and its consequences are directly linked to the underlying condition. For example, a collapse or a deformation causes a conduit cross-section reduction, which can lead to decreased hydraulic performance. However, only a collapse can also lead to exfiltration or infiltration. Furthermore, the causes that lead to these conditions can be completely different. We therefore assume that the reliability of sewer condition
predictions may improve if the predictions are based directly on closed circuit television (CCTV) observation data instead of condition classes. In this context, Dirksen & Clemens (2008) have found a lack of direct relation between age and condition class. They also suggested basing transition oriented models on CCTV inspection data.

The state of the art CCTV coding system to describe sewer conditions in central European countries is EN 13508-2/A1 (CEN 2010). For German speaking countries, this code was implemented in the working aid for sewer classification ISYBAU (OFD 2010). Therein, the identified conditions are pre-classified according to three failure categories ‘structural stability’, ‘operational safety’ and ‘impermeability’. A similar system is used in the Netherlands, where the recorded conditions are ordered according to three aspects, ‘leak tightness’, ‘stability’ and ‘flow’ (Dirksen & Clemens 2008).

In both systems, the observed conditions, like displacement, deformation, collapse, etc. are numerically classified from 1 (small impact) to 5 (strong impact) with respect to the aforementioned categories/aspects. If an observation is not relevant for one of the categories, it is attributed classification 0. Using this pre-classification scheme, as a basis for sewer degradation prediction, offers the possibility for a more cause and effect oriented prediction.

This paper is structured as follows. First, we introduce a method to derive models for predicting sewer degradation based on data from partially inspected sewer systems. Building on this, we describe a cause and effects oriented sewer performance evaluation approach with respect to the functional requirements given in EN 752 (CEN 2008) and the three failure categories given in ISYBAU (OFD 2010). This evaluation is introduced as a decision support to prioritize sewers for inspection and to choose appropriate inspection techniques. In the results section, we show the exemplary application of the predictions to an Austrian sewer system. We derive regression models based on both failure category and condition class data. Next, we compare the models regarding their accuracy by applying them to a validation dataset. As an example for analysing the effects of sewer degradation, the hydraulic performance of sewers under collapse condition is calculated.

**MATERIALS AND METHODS**

**Binary logistic regression models for sewer degradation prediction**

Regression models in general have a strong potential to describe the relationship between a response variable (cause) and one or more explanatory variables (intrinsic and surrounding conditions). The binary logistic regression model (BLR) is described as one preferred regression model in sewer deterioration modelling (Ariaratnam et al. 2001; Davies et al. 2001; Ana & Bauwens 2010). The BLR describes the relationship between a binary outcome variable \( y \) and a set of covariates \( (x_1, \ldots, x_k) \). The main characteristic of the BLR is that \( y \) is not modelled directly but the probability associated with the values of \( y \) is provided. Given that \( y \) has values of either 1 or 0, the hypothetical population proportion of cases for which \( y = 1 \) is defined as \( \pi = P \ (y = 1) \), and the proportion of cases for which \( y = 0 \) is \( 1 - \pi = P \ (y = 0) \). The probability that \( y \) is equal to 1 is calculated with Equation (1):

\[
\pi = P(y = 1) = \frac{\alpha + \sum_{i=1}^{k} \beta_i x_i}{1 + e^{\alpha + \sum_{i=1}^{k} \beta_i x_i}} \tag{1}
\]

where \( \alpha \) is the intercept parameter (or constant) and \( \beta \) represents the logistic regression coefficients for the covariates \( (x_1, \ldots, x_k) \). Ana & Bauwens (2010) and Hosmer & Lemeshow (2005) give a more detailed overview about logistic regression analysis.

Following ISYBAU (OFD 2010), the observed conditions from CCTV inspections are pre-classified into 6 classes (0-5) regarding their relevance for the failure categories ‘structural stability’, ‘operational safety’ and ‘impermeability’. To make these pre-classified condition data useable for a BLR analysis, the data have to be assigned to the binary variable \( y \). For example, if the failure category ‘structural stability’ is analysed, the variable \( y \) is assigned as follows. For all records of the dataset, which were classified as a 4 or 5 condition state regarding ‘structural stability’, the variable \( y \) is assigned to the value 1. For all other records, \( y \) was assigned to the value 0.

**Cross validation to derive robust regression models**

The ratio of records with values \( y = 1 \) to values \( y = 0 \) in sewer condition datasets is generally very small. This can result in a low overall performance of the regression model. Therefore, to derive robust models, we chose the following cross validation procedure:

1. Count the amount of records where \( y = 1 \) in the sewer condition dataset and select these records from the dataset.
2. Randomly select as many records from the dataset with values \( y = 0 \) as counted in (1).
3. Combine the records selected in (1) and (2) to build a random sample.
4. Derive a regression model based on the random sample that fits the data best. Therefore, the significant covariates and the associated regression coefficients are derived using a maximum likelihood estimator and a stepwise forward model building process. In this process, one covariate after the other is added and one model after the other is compared with the start model by calculating the $-2 \log$ likelihood ratio. Only covariates which cause significant changes in the $-2 \log$ likelihood ratio are used in the model.
5. Predict the failure probability for the entire system with the derived regression model.
6. Repeat step (2) to (5).
7. Verify the n-built models according to the following criteria:
   (a) Similar significant covariates.
   (b) Evaluate the prediction results of the entire system with a receiver operation characteristics (ROC) diagram, by comparing the ratio of the right hits (sensitivity) with the ratio of false alarms (1 – specificity) at a defined cut-off (here, 0.5).
   (c) If the ROC of the models tend to have similar values, the random data sampling is stopped.
8. If the comparability is given according to (7), the final model is built by calculating the average regression coefficients of the models with the best ROC results.
9. The final failure model is used to calculate the probability of the failure types of interest for the entire sewer system and can be further used for the cause and effects sewer degradation evaluation.

To analyse the benefit of this cross validation process in contrast to models which are based on the original dataset, we compare the performance of the cross validated model with an ‘all data’ model, also using an ROC diagram. For the model based on the original dataset (‘all data’ model), the hit rate vs. false alarm rate is calculated for the optimal cut-off value. The optimal cut-off value is given when the sensitivity (right hits) as well as the specificity (true negatives) reach a maximum.

To validate the differently derived models we applied them to areas where CCTV inspections have already been undertaken, but which were not used for model calibration.

**Sewer section performance evaluation to support inspection planning**

A performance-oriented evaluation of sewer sections can be realised by a combined examination of failure probabilities and potential negative effects resulting from the predicted failure. The aim of such an evaluation is to identify sewers, which both have a high failure probability and may cause a performance reduction regarding functional requirements under failure conditions. General functional requirements of sewer systems are defined in EN 752 (CEN 2008). The failure categories we take into account in this paper follow the categorization of ISYBAU (OFD 2010).

Table 1 shows the failure categories and performance measures that should be investigated for a cause and effects oriented sewer evaluation.

The effects of sewer failure on the hydraulic performance of a sewer system can be assessed by means of VulNetUD (Möderl et al. 2009; Fuchs-Hanusch et al. 2012; Kleidorfer et al. 2013). VulNetUD is a tool based on SWMM5 (Gironás et al. 2010), which allows a one at a time sensitivity analysis of sewer section failure (Möderl et al. 2009). The hydraulic performance, under conduit reduction, is analysed by quantifying an increase in flooding and in outflow to receiving water bodies.

Evaluating possible impacts on subsurface water bodies due to sewer impermeability, the distance between the groundwater layer and the sewer system can be used as a simple measure for an effects evaluation. Furthermore, to take into account a possible endangerment of adjacent subsurface infrastructure, like gas or water supply pipelines, caused by a sewer collapse, spatial buffering can also be used.

We assume that sewer sections, which cause negative effects on sewer performance under failure conditions and additionally have a high probability of failure, should be

<table>
<thead>
<tr>
<th>Components for evaluation of sewer sections</th>
<th>Flooding wet weather</th>
<th>Flooding dry weather</th>
<th>Adjacent infrastructure</th>
<th>Environmental impacts subsurface water</th>
<th>Environmental impacts surface water</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probability Collapse</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Impermeability</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>Operational problems (e.g., blockage)</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>

Table 1 | Components for evaluation of sewer sections based on ISYBAU (OFD 2010) and EN 752 (CEN 2008)
inspected frequently using high quality CCTV. For sewer sections where failure will cause only minor performance reductions, we suggest that simple and cost-saving inspection techniques, like manhole zoom-camera inspections, can also be applied as a first option (Plihal et al. 2014).

**Case study system**

The case study system is a partial system of a sewer network of approximately 800 km. It comprises 4,577 conduits with a total length of 141 km and was completely inspected with CCTV between 2008 and 2009. In addition to CCTV data, information on condition class, material, vintage, sewage type, profile type, width, height, length and depth of the sewers was available for each sewer section.

To build and test the regression models, the sample system was separated into two parts. One part (abbreviated as Area A) was used to calibrate the failure conditions. Area A consists of mainly circular combined sewers in concrete and stoneware. Some newer sections were built in ductile iron. The oldest sections are around 100 years old. Around 25% are older than 50 years. A large number of sewers were built in the late 1980s and early 1990s. For older sewers, the age had to be estimated in ~10-year steps. Therefore, the data were structured into age categories (Table 2).

Area B has a slightly different structure according to age, as approximately 50% of the sewers are older than 50 years. Similar to Area A, most of the sewer sections were built in concrete and stoneware.

A hydraulic model with a length of 43 km was available for a partial system in Area A. This model was adapted for use in VulNetUD to derive hydraulic performance reductions caused by sewer degradation.

**RESULTS**

**Data preparation and model building for failure category/condition class predictions**

To test and verify our approach, we applied the described methods to the failure category ‘structural stability’. In Area A, from 2,832 records in total, 252 records belong to condition class 4 and 5 regarding ‘structural stability’.

<table>
<thead>
<tr>
<th>Covariates</th>
<th>$\beta$ (all data)</th>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>$\beta_3$</th>
<th>$\beta_4$</th>
<th>$\beta_5$</th>
<th>$\beta_6$</th>
<th>Frequency in dataset (nominal covariates)</th>
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<td>Length</td>
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<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>96</td>
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<tr>
<td>Material</td>
<td>AC (reference)</td>
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<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>6200</td>
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<tr>
<td></td>
<td>BS</td>
<td>-0.79</td>
<td>0.45</td>
<td>-1.50</td>
<td>-0.64</td>
<td>-1.22</td>
<td>-1.16</td>
<td>-2.34 28</td>
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<td></td>
<td>CI</td>
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<td>-20.19</td>
<td>-20.52</td>
<td>-20.61</td>
<td>-20.51</td>
<td>-20.90</td>
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<tr>
<td></td>
<td>Con</td>
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<td>1.89</td>
<td>0.55</td>
<td>0.50</td>
<td>0.47</td>
<td>0.51</td>
<td>0.21 1006</td>
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<tr>
<td></td>
<td>DI</td>
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<td>-2.32</td>
<td>-2.20</td>
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<td>-2.31</td>
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<td>-1.27</td>
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<td>-1.45</td>
<td>-1.06</td>
<td>-0.34</td>
<td>-2.24 58</td>
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<tr>
<td></td>
<td>P</td>
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<td>-0.52</td>
<td>-0.64</td>
<td>-1.02</td>
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<td>-1.42 103</td>
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<td>0.33</td>
<td>-0.08</td>
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<td>-0.47</td>
<td>-0.29</td>
<td>-0.89 1011</td>
</tr>
<tr>
<td>Profile</td>
<td>Ovoid (reference)</td>
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<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>175</td>
</tr>
<tr>
<td></td>
<td>Mouth</td>
<td>1.05</td>
<td>1.13</td>
<td>0.93</td>
<td>0.37</td>
<td>1.09</td>
<td>1.22</td>
<td>1.20 400</td>
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<tr>
<td></td>
<td>Circular</td>
<td>-0.22</td>
<td>-0.81</td>
<td>-0.89</td>
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<td>-1.07</td>
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<td>Width</td>
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<td>-0.01</td>
<td>-0.01</td>
<td>-0.01</td>
<td>149</td>
</tr>
<tr>
<td>Vintage</td>
<td>1913 (reference)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>149</td>
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<tr>
<td></td>
<td>1929</td>
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<td>1.10</td>
<td>0.73</td>
<td>1.17</td>
<td>1.56</td>
<td>1.23</td>
<td>1.20 535</td>
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<td></td>
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<td>-1.09</td>
<td>-1.19</td>
<td>-1.58 57</td>
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<tr>
<td></td>
<td>1974</td>
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<td>0.27</td>
<td>0.38</td>
<td>0.12</td>
<td>0.03 861</td>
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<tr>
<td></td>
<td>1994</td>
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<td>-0.33</td>
<td>-1.06</td>
<td>-0.73</td>
<td>-0.70</td>
<td>-0.22</td>
<td>-0.69 1165</td>
</tr>
<tr>
<td>Constant</td>
<td>$\alpha$</td>
<td>-1.51</td>
<td>1.56</td>
<td>2.26</td>
<td>3.06</td>
<td>2.49</td>
<td>1.80</td>
<td>2.83</td>
</tr>
</tbody>
</table>

Table 2 | Covariates and derived regression coefficients for six random models and the ‘all data’ model for the failure category ‘structural stability’
Therefore, the value \( y = 1 \) of the binary outcome variable was assigned to these 252 conduits. Next, random samples were built as described in the methods section. For the first six random samples, the significant covariates turned out to be material, length, width, vintage and profile. The two other tested covariates, depth and sewage type, have shown significance levels bigger than 0.1. Table 2 shows the regression coefficients for the six random models and the ‘all data’ model. With Equation (1) and the regression coefficients provided in Table 2, the failure probability can be calculated for all pipes in the entire sewer systems.

To compare the performance of the introduced failure prediction model with a condition class-based model, random models were derived similarly for the condition class data. Therefore, the binary outcome variable was formed based on the classification provided in the sewer section data. Therein, five classes are listed. Classes 4 and 5 represent a high level of degradation and are converted to the binary outcome variable \( y = 1 \). Class 3–1 are converted to the binary outcome variable \( y = 0 \).

To analyse the comparability of the random models, the ROC levels, which are reached if the models are applied to the entire dataset of Area A, are calculated. Generally, the models reach very good hit and low false alarm rates in the calibration area, with slightly better hit rates for the failure category based models (Figure 1(a)).

From Figure 1, it can be further derived that the ROC values of the random models are very close to each other for both the CCTV data-based models (Figure 1(a)) and the sewer section data-based models (Figure 1(b)). Therefore, it can be assumed that the random models are comparable. The average regression coefficients \( \beta_{av} \) from Model 1 to Model 6 are used to build final models for additional tests in the validation area of the case study system.

**Model validation and comparison of models with different data basis**

Next, the potential of the differently derived models to predict failure modes of the category ‘structural stability’ and condition classes of the category ‘4 and 5’ in the entire sewer system, was analysed. Therefore, the models built with the average regression coefficients \( \beta_{av} \), abbreviated as ‘cross validated failure category model’ and ‘cross validated condition class model’, were applied to the sewers of Area B. In addition, the ‘all data’ models, abbreviated as ‘optimal cut-off failure category model’ and ‘optimal cut-off condition class model’, were applied to this system. The optimal cut-off values for the ‘all data’ models have to be derived from the application of the models to the calibration dataset.

To analyse the model performance in the validation area, we also evaluated the models with an ROC analysis (Figure 2). In this analysis, the ‘cross validated failure category model’ reached the highest hit rate, but also the highest false alarm rate. Nevertheless, if we assume that in a cause and effects oriented approach, the utility prefers to be on the safe side, the performance of this model is still better in contrast to the other models.

Figure 2 shows that the condition class-based models are very close to a random guess, which is given when the hit rate and the false alarm rate have similar values (diagonal line). Therefore, the models are not recommended for further use in planning inspections of the entire sewer system.
Effects of a sewer collapse on hydraulic performance

As an example for analysing the effects of structural sewer degradation on the overall sewer performance, we analysed the hydraulic performance reduction due to sewer collapse. Therefore, both for dry weather (DW) and storm water (SW) flow, the vulnerability of sewers in a partial system of Area A was assessed with respect to flood volume and overflow to surface waters.

Figure 3(a) shows the volume of flooded DW flow caused by a full conduit reduction of the specific sewers. The sewer at the end of the partial system, but before a combined sewer overflow, causes the highest DW flood volume in the system under collapse condition. There are two other sections of the main sewer, which cause flooding at DW flow under collapse simulation. There, the level of backwater is lower than the level of weirs. Figure 3(b) highlights sewers in black and thick line width that induce a high outflow volume. Again, the main sewer is affected because of the high flow rate. As can be seen, collapsed sewers that induce an increase of outflow have no effect on flood volume and vice versa, but the vulnerable regions are similar (main sewers close to outflow structures). Similar results were reached for a wet weather flow simulation.

Inspection prioritization based on sewer failure effects evaluation

By spatial overlay of failure probability maps and, for example, hydraulic vulnerability maps, sections most likely to fail and also lead to a performance reduction can be identified. In the example network, the failure category ‘structural stability’ was analysed in detail. We applied the evaluation approach to the partial system (43 km) of Area A, where the hydraulic model was available. For 2.3 km out of these 43 km sewers, failure modes belonging to the category ‘structural stability’ can be expected. Among these conduits, around 600 m will cause a significant increase in flood volume under collapse conditions at wet weather flow. Two segments of these 600 m can also lead to flooding at DW conditions. None of the vulnerable sewers, according to an increase in overflow, has shown a high collapse probability.

With respect to the introduced performance-based inspection planning approach, we suggest that these 600 m...
should be inspected more frequently than the current suggestion of European standards, which is once in 10 years. Furthermore, we think, that these segments require a high quality of CCTV inspection. Conversely, we suggest that the high number of segments with low failure probabilities, as well as low hydraulic vulnerability, can be first inspected with simpler techniques like manhole zoom-cameras. Based on the results of such a first cost-saving inspection, an additional high-resolution CCTV inspection can follow for conspicuous sewers.

CONCLUSIONS

In this paper, we showed how a cause and effects oriented sewer degradation evaluation can be used to support scheduled CCTV inspection planning. Therefore, we introduced an approach that led to robust regression models for failure prediction. We applied this approach to an Austrian sewer system, and derived and validated models for the prediction of failure categories as well as for conventional sewer condition classes.

The results have shown the following:

1. A good performance of the models, which were derived following a cross validation process. The good performance was reached for both the condition class and the failure category predictions.
2. That the models, built with the introduced cross validation process, perform better than those which categorize the outcome variable $y$ based on the optimal cut-off value.
3. That the performance of the models based on sewer condition class data was not satisfying when applied to a validation area of the entire sewer system.

We conclude that the suggested failure category-based prediction, which bases the regression analyses directly on CCTV data of a partially inspected system, has a strong potential to predict similar conditions in the entire system. To achieve this, a first high quality CCTV inspection in a partial system with a wide range of different sewer types is essential. A drawback of the approach is the need for these high quality CCTV data. In addition, the approach requires a pre-classification of condition data according to different failure categories, which is not yet supported by available CCTV data interpretation software.

Nevertheless, such a pre-classification is of additional benefit, if an advanced sewer performance evaluation is of interest, like hydraulic capacity or overflow calculations under failure conditions. By spatial overlay of, for example, collapse probability maps with hydraulic vulnerability maps, the sewers that are most likely to cause a performance reduction can be highlighted. Following this performance-oriented sewer evaluation allows focussing high quality CCTV inspections on the most critical segments in the entire system.

To avoid neglecting operation and maintenance of segments with low failure probability and vulnerability, we suggest first using simple inspection techniques like manhole zoom-cameras, to be followed up by CCTV inspection if conspicuous segments are identified. We assume that such a targeted inspection can lead to cost savings, but still follow the tasks of a performance oriented sewer maintenance, as recommended in EN 752 (CEN 2008).

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