A study of influential parameters and different sewer blockages

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Highlights

- Bayes theorem was used to investigate four parameters and their influence on the likelihood of blockages.
- The dataset post-processing contained over 38,500 blockages formed 2012-2019 in the United Kingdom.
- The data contains five separate failure modes of blockages - paper/rag, non-sewer debris, fat, roots, silt.

Introduction

Sewer blockages result in reduced network functionality, flooding and pollution incidents leading to public health risks and reputational damage for water companies. Water UK estimates removing blockages costs £100 million each year in the United Kingdom. As blockages are resolved, information is collected which is useful in understanding influential parameters like pipe diameter, gradient and material. This understanding informs asset rehabilitation or replacement, new standards and regulations and new insights in research. Previous studies have used this information to understand what causes blockages (Arthur et al., 2008; Ugarelli et al., 2010) and make predictive models (Rodríguez et al., 2012; Bailey et al., 2015). In previous studies the limitations of the underlying datasets have normally meant blockages of different natures have been considered together without differentiation by mode or composition. However, one paper did analyse data in which sediment blockages were considered separately in manholes, gully pots and pipes (Rodríguez et al., 2012). This study analyses a dataset which allows a novel differentiation by composition. The aim of this research is to better understand the influence of pipe length, diameter, depth of cover and material on five blockage modes - paper/rag, non-sewer debris, fat, roots and silt blockages.

Methodology

This study analyses over 38,500 blockages formed 2012-2019 in the United Kingdom. The pipe length, diameter, depth of cover and pipe material have been investigated as influential parameters. These four parameters were selected because they were common to both datasets required by the Bayes methodology. The two datasets are labelled here as dataset 1 and dataset 2. Dataset 1 contained the details for blocked pipes between 2012-2019. Dataset 2 contained the details for unblocked and blocked pipes in the same region. Prior to processing, dataset 1 contained 49,019 historical blockage records and dataset 2 contained 972,123 network asset records. The datasets were cleaned before analysis. The cleaning process involved filtering for relevance (blockages, sewer assets only, reactive responses to events) and filtering for quality (removing default values, duplicates and typos). Data associated with each parameter was converted such that it was all the same format. Finally, blockage records were only taken forward for analysis if they included a measurement of pipe length. The pipe length allows calculating the length weighted blockage rate - the standard metric in associated research literature. After cleaning the data, dataset 1 contained 38,585 records and dataset 2 contained 319,624 sewer assets.

Following data cleaning discrete classes for each parameter were decided. Acrylonitrile butadiene styrene plastic, medium density polyethylene, high density polyethylene, glass reinforced plastic, Alkathene, molecular orientated polyvinyl chloride and polyork were grouped together and classified as plastics. Cast iron, ductile iron, steel, galvanised iron, spun iron and copper pipes were classified as metallic pipes. Gully pot blockages and blockages in short pipes less than 1 meter were removed from the analysis because they are of a different nature to the other blockages and complicated weighting blockages by pipe length in

dataset 1. Thus, pipe length classes began with 1-10m. Other classes were aggregated to expand the scale for the region of interest along the x axis. This resulted in pipe length classes of 50-100m, 100-500m and 500-1000m. The diameter and depth of cover classes were defined in a similar fashion.

Bayes theorem was used to calculate the posterior probability across the four parameters for five blockage modes - paper/rag, non-sewage debris, fat, roots and silt blockages. In the context of this study the "posterior probability" is comparable to the likelihood of blockage caused by each parameter independently. The posterior probability is useful because it is independent of disproportionate network specifications - how some classes like vitrified clay pipes make up many of the assets and have more blockage records because of their majority representation. These posterior probability distributions for five blockage modes across the range of the four parameters have been compared directly with the probability of blocked assets being of any single class. The probability of blockages being of any single class only uses the information in dataset 1 and shows the raw data distribution before applying Bayes theorem.

$$P(X|Y) = \frac{P(Y|X) \cdot P(X)}{P(Y)}$$

In the context of this study P(X|Y) is the probability of blockage given that the pipe is of a certain class Y. P(Y) is the probability that any pipe is of class Y and P(Y|X) is the probability that a pipe is of class Y given that a blockage formed in that pipe. P(Y) and P(Y|X) could be calculated using dataset 2 and dataset 1 respectively. For the prior belief, P(X), a uniform probability distribution was assumed across the range of all parameters. This assumption was made blind to the data and the deviation from this model given the new information found in the data produces the updated belief which shows the influence across the range of a parameter. P(X), P(Y), and P(Y|X) were combined using Bayes theorem to calculate the posterior probability, P(X|Y), for the five blockage modes across the range of four parameters. These five series are compared directly with P(Y|X) for blockages of all compositions.

Results and discussion

Figure 1 shows the normalised posterior distributions for five blockage modes, series names prefixed "B:", along with one series showing the normalised raw data distribution for all blockages, series name prefixed "A:". Line plots were used in figure 1 to aid following and comparing series however it should be noted that there is only one data point for each class for each series and interpolating between classes like "metallic" and "concrete" is not meaningful. For normalisation each series has been scaled such that the sum of the y coordinates is equal to one. Normalising the series allows direct comparison between different series.

The first highlight of figure 1 is that the benefits of Bayes methodology are demonstrated in analysing figure 1 (c) and (d). In these two sub-plots the posterior distributions diverge from the "B: all blockages" series. For example, the "B: all blockages" series suggests vitrified clay pipes are most likely to block. The Bayes series for material using information in dataset 1 and 2 shows that dataset 1 on its own is misleading and that pitch fibre pipes are more likely to block than vitrified clay pipes. This shows that applying Bayes methodology and adding the information from dataset 2 to dataset 1 is important in a sewer blockages context. The inverse trends for length and diameter support what is already found in the literature. Figure 1 (c) shows that depth of cover also shares an inverse trend with blockage likelihood and pitch fibre pipes are shown to be more likely to block than any other pipe material for all blockage compositions.

Finally, the results in figure 1 show that all modes of blockage show similar trends across pipe length, diameter and depth of cover. However figure 1 (d) shows that blockage modes diverge in pipes of different materials. For example, silt blockages are significantly more likely to block than any other blockage mode in metallic pipes. This agrees with the known phenomenon of encrustation around metallic joints. This means blockages of different compositions behave in a similar fashion with regards to geometry and depth of cover but have more complex interactions with pipe material.

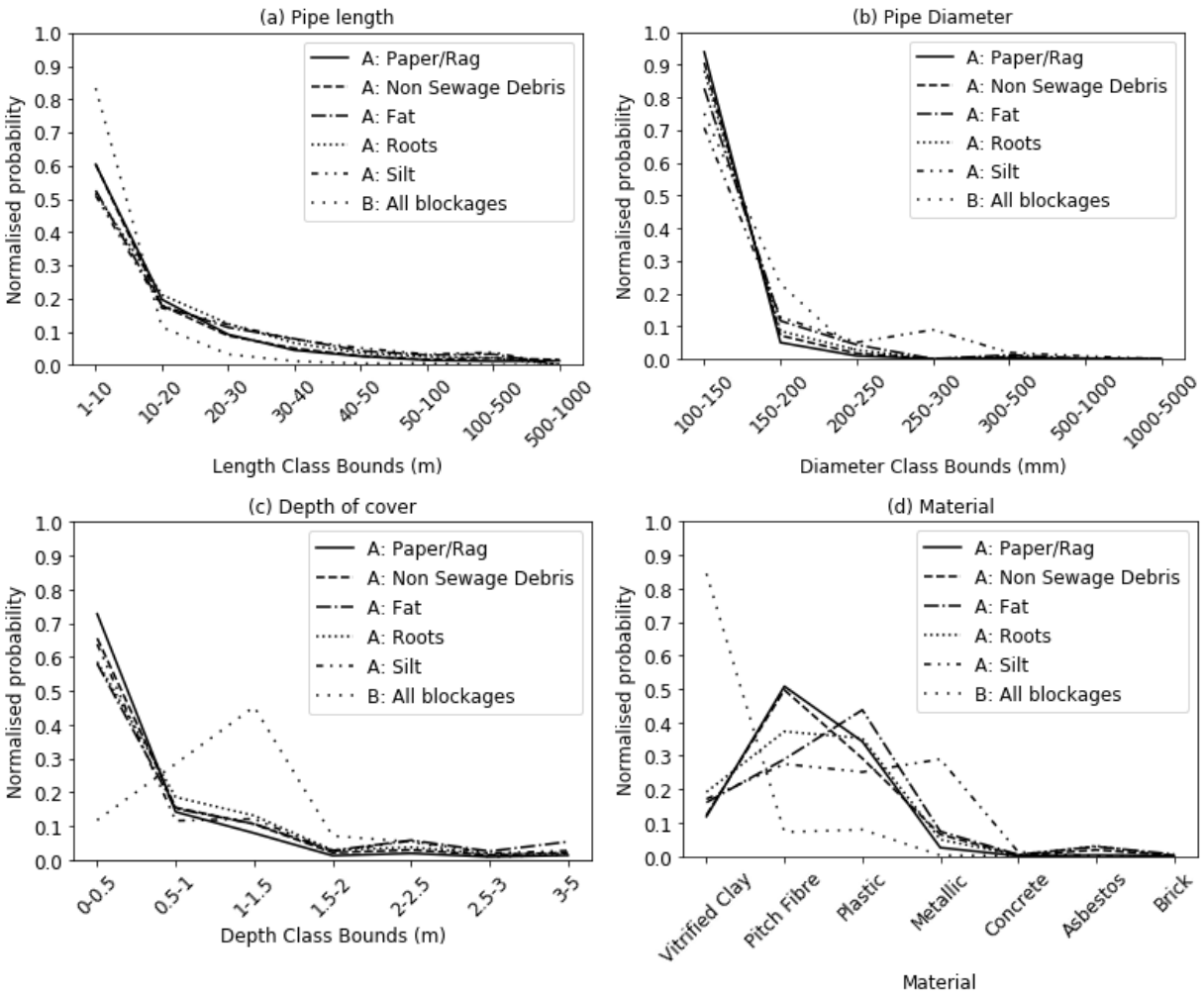

Figure 1: Graphs showing the normalised probability of blockages in dataset 1 with the normalised posterior probability for the five modes of blockage across the four parameters: (a) pipe length, (b) pipe diameter, (c) depth of cover and (d) material

Conclusions and future work

Using a novel breakdown of blockage modes this study has shown that blockages of different compositions show similar trends for pipe length, diameter and depth of cover. In addition, this study shows that in pipes of different material blockages of different composition behave differently. Bayes methodology has also been validated in a sewer blockages context. Further research in this field includes repeating the analysis in this study for the five blockage compositions on variables like land use or housing density. Furthermore, the analysis should be expanded such that variables are not handled independently and the most influential parameter identified. Finally, composite variables for different blockage mechanisms should be identified.

References

Arthur S., Crow H. and Pedezert L., (2008), Understanding blockage formation in combined sewer networks, *Proceedings of the Institution of Civil Engineers-Water Management* Vol. 161, No. 4, pp. 215-221, DOI: https://doi.org/10.1680/wama.2008.161.4.215

Bailey J., Keedwell E., Djordjevic S., Kapelan Z., Burton C. and Harris E., (2015), Predictive risk modelling of real-world wastewater network incidents, *Procedia Engineering*, 119, pp.1288-1298, DOI: https://doi.org/10.1016/j.proeng.2015.08.949

Rodríguez J.P., McIntyre N., Díaz-Granados M. and Maksimović Č., (2012), A database and model to support proactive management of sediment-related sewer blockages, *Water research*, 46(15), pp.4571-4586, DOI: https://doi.org/10.1016/j.watres.2012.06.037

Ugarelli R., Venkatesh G., Brattebø H., Di Federico V. and Sægrov S., (2010), Historical analysis of blockages in wastewater pipelines in Oslo and diagnosis of causative pipeline characteristics, *Urban Water Journal*, 7(6), pp.335-343, DOI: https://doi.org/10.1080/1573062X.2010.526229

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