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Assessing impacts of the private sewer transfer on UK utilities

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In October 2011, Section 105A (S105A) of the Water Act of 2003 transferred the ownership of previously privately owned sewers to the ten water and sewerage companies operating in England and Wales. In light of this recent legislative change, this paper discusses the asset management challenges associated with the private sewer transfer before exploring a decision-making framework used by South West Water to establish a more accurate understanding of the extent and likely condition of their newly transferred network. The framework has allowed South West Water to initiate a proactive asset management programme with the aim of addressing the deteriorating condition of these assets while also tackling their associated serviceability performance. Initially, a number of geospatial (GIS) tools are used to provide an estimate of the likely extent of the transferred network before a well-established public sewer deterioration model is used to predict the condition and operational performance of these S105A assets over time. The outputs from this study have better equipped decision makers with information surrounding the deterioration and collapse rates of these newly transferred sewers over time. The information has been used to help formulate strategic business planning decisions, for example, by using cost vs. benefit analysis tools to model different investment scenarios across the network.

Notation

- C_c constant coefficient to account for third party incidents (nr/km/year)
- C_i coefficient by condition grade (nr/km/year)
- L total sewer length by cohort (km)
- P_i proportion of sewer length in respective condition grade (%)
- λ sewer collapse rate (number/year)

Legislative background

Section 105A (S105A) of The Water Act 2003 (2003) introduced a new legislation to the Water Industry Act 1991 (1991), which gave the UK government the power to require sewerage undertakers to adopt privately owned sewers and lateral drains in England and Wales. Since 2003, the ten statutory water and sewerage companies operating in England and Wales had all recognised that the transfer of these assets would significantly impact their companies' existing resources, and further concerns had been raised surrounding the likely condition and operational performance of these assets (Stimpson, 2011). Prior to transfer, the UK government's Department for Environment, Food and Rural Affairs (Defra) had estimated that approximately 154 000 km of privately owned sewers would be transferred in terms of responsibility to the water companies, which is an increase of approximately 50% in sewerage assets per utility provider (Defra, 2007). In February 2007, the government announced its decision to proceed in principle with the transfer (Pearson, 2007), which was later affirmed in a statutory instrument known as The Water Industry (Schemes for Adoption of Private Sewers) Regulations 2011 (HMG, 2011). This legislation enforced the transfer of responsibility for privately owned sewers and lateral drains that connect to the public sewer network from the 1st of October 2011. Figure 1 shows the typical drainage arrangements for the transferred sewer assets, which are henceforth referred to as S105A sewers. Prior to the transfer, these S105A sewers were the responsibility of the homeowner(s) unless they were constructed prior to 1 October 1937. For the avoidance of doubt, the only sewers or lateral drains in England and Wales that were classified as being in private ownership were those constructed after 1 October 1937. This reflects the previous adoption of privately owned sewers constructed before this date under Section 24 of the Public Health Act 1936 (1936).

Challenges

The lack of data surrounding the condition of buried water and wastewater infrastructure is often the main obstacle in the deployment of an effective asset management strategy (Vangdal and Reksten, 2011). This is even more prevalent in the case of the private sewer network in England and Wales due to the very recent change in ownership from the customer to the utility provider.

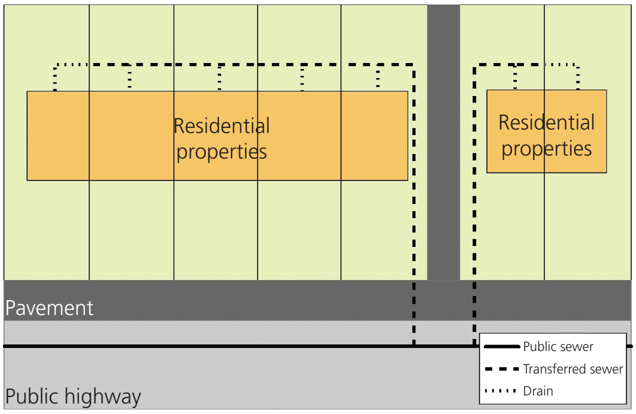

Figure 1. Typical S105A drainage arrangements

Water UK (2013) acknowledges that basic information for these newly transferred assets, such as asset location, condition, basic attribution and maintenance history, is largely unknown and the mapping costs alone have been estimated to be as high as £118 million (Defra, 2007).

In light of these findings, some water companies have already begun an extensive mapping and record-keeping programme for these assets, involving the digitisation of historic plans from local authorities and the use of in-field data capture to locate unmapped assets, leading to closed-circuit television (CCTV) condition surveys to better understand asset performance. Information of this nature is extremely valuable, although it is no surprise that it is costly to obtain and unlikely to cover the entire network for quite some time. Therefore, the need for cost-effective decision-support frameworks capable of integrating all available data into a single framework to help asset managers make complex investment decisions has been acknowledged as a high-priority area for future research (Awwarf, 2008). Ideally, such tools would be founded on the use of geospatial approximation techniques to quantify the extent of the transferred network, coupled with a deterioration or collapse model to simulate asset performance.

A number of UK water and sewerage companies were involved in an unpublished study undertaken by the Water Research Centre (WRc) for UK Water Industry Research (UKWIR, 2002). This study helped to produce a high-level model that could be adapted by each water company to provide their own local estimates for private sewer lengths, work volumes and costs. UKWIR (2002) captured the approach in an unpublished document 'The Real Cost of taking over Private Sewers and Drains'. The foundations of the UKWIR model are centred on the following: the number of households within each utility provider's service area; the property type of these households, that is, detached, semi-detached and terrace; and the property age range. Using this information, the model assigns typical average lengths for drains and sewers to form an overall estimate for network length, which is subsequently used in a secondary model to estimate the nature and extent of the work required to manage these drains and sewers appropriately.

While the UKWIR model has served its original purpose by providing a mechanism to estimate the likely extent and potential financial impact of the newly transferred sewers, the top-down approach is considered too crude for rigorous business planning with margins of error cited to be in the region of ±40% (Sanderson, 2012). Furthermore, it does not provide a mechanism to model the performance of these assets based on known or predicted asset condition, and it is even more difficult to prioritise investment programmes toward poorly performing assets due to the top-down nature of the modelling process. As a result, utility providers are now looking to apply more comprehensive deterioration and collapse models that have been established using a variety of different techniques over time, for example, logistic regression (Ariaratnam *et al.*, 2001), exponential models (Wirahadikusumah *et al.*, 2001), time- and state-based Markov models (Baik *et al.*, 2006; Kleiner and Rajani, 2001), fuzzy-based techniques (Kleiner *et al.*, 2006) and more recently through machine learning such artificial/neural network models (Najafi and Kulandaivel, 2005) and evolutionary computing techniques (Savic *et al.*, 2006). One common theme through all of the above literature is the importance of data aggregation into homogenous pipes groups, although this is often highly governed by the availability and quality of data across the network (Savic *et al.*, 2009).

Data availability and quality are also two of the governing factors currently presenting a real barrier to the successful deployment of effective asset management techniques for the newly transferred private sewer network, or in fact any asset base whereby information surrounding the extent, attribution and condition of the asset stock is limited. To overcome this knowledge gap, an end-to-end asset management methodology has been developed for South West Water, who provides wastewater services across an operational area of 11 137 km^2, which encompasses 1·6 million residents served by around 14 800 km of public sewers (South West Water, 2013). At the time of this study, 2452 km of newly transferred private sewers had already been mapped and reasonably well attributed by the business. Therefore, the subsequent sections of this paper describe the methodology that was applied to estimate the extent, condition and business investment needs to manage the unmapped and unattributed S105A network. It was later estimated from this study that South West Water's existing mapping (2452 km) formed 39% of their overall transferred network length.

Modelling the extent of the S105A transferred network

To help develop an improved understanding of the newly transferred private sewer network, the authors have developed a universal approach that can be integrated with any corporate GIS system to provide the foundations of a successful asset management strategy. The methodology presented here differs from the UKWIR approach (2002) by making estimates for the S105A sewer length at the individual property level. This is achieved by using widely available geospatial data sets in the form of OS MasterMap Topography and AddressBase layers. These datasets are interrogated by the model and used to geospatially position a 'notional' sewer connection between each property group and the nearest applicable public sewer (Figure 2).

Due to the nature of the digitisation process used for the mapped S105A sewers, a single private sewer that connects from the property group to the public sewer is likely to consist of multiple sewer spans connected between manholes. Therefore, to ensure that the notional sewer is compared to a single length that represents the entire extent of the private sewer length, all interconnected sewer spans are joined together where a common manhole is shared. Furthermore, to accommodate the nature of private sewers whereby more than one property connected by a shared boundary is served by a single S105A sewer, a number of property groups are established in GIS. This is achieved by merging common property boundaries to create a single property group polygon from the OS MasterMap data (Figure 2).

Each property group, created using the above process, is then attributed with the number of merged properties in order to determine the property group type, that is, terrace property groups that encompass more than two properties. Once all of the property groups have been formed, the centroid of the group is used to create the notional asset connection by taking the most appropriate straight-line path to the nearest public sewer. A connection is created for both the surface water drainage and the foul-combined sewerage. While it is not strictly true that all properties will have separate surface water drainage arrangements, further downstream processes involve cross-checking the utility providers' customer billing information and estimating the likelihood of a soakaway being present to remove the surface water sewers from those properties with soakaways or combined drainage arrangements. Figure 1 provides a visualisation of the network pre- and post-processing. The benefit of this approach is that the geospatial proximity of a property group to the public sewer network is considered during the estimate of the S105A sewer length.

The process of calibrating the model is two phased. First, a complete set of notional assets is created for each property group across the entire network. Second, the notional asset lengths are compared in controlled areas where existing and accurate mapping already exists for these assets. Notional assets in these areas are only used for the purposes of calibrating a series of coefficients and are later removed from the overall network analysis. The coefficients are used to estimate the length of the unmapped areas by being applied as multiplication factors against the notional straight-line distances. Nine coefficients were calibrated for each sewer function (foul combined and surface water) to account for the differing drainage arrangements due to property type (detached, semi-detached, terrace) and property age (1937–1969, 1970–1999, >1999). These age bands were selected to provide an even coverage for S105A sewers, that is, those sewers laid post 1937 and up until the present day. The dates were also governed by the availability of historic mapping data and property age classifications provided by the UK government evaluation office agency. This coefficient-based approach is deemed to be more representative of the actual drainage arrangement because it is able to account for the geospatial features associated with each individual sewer, that is, property distance to public sewer. The model is calibrated by adjusting each modelling coefficient to minimise the overall error across the region between the observed and notional sewer lengths. The statistical results of the model calibration process for each coefficient are captured in Table 1.

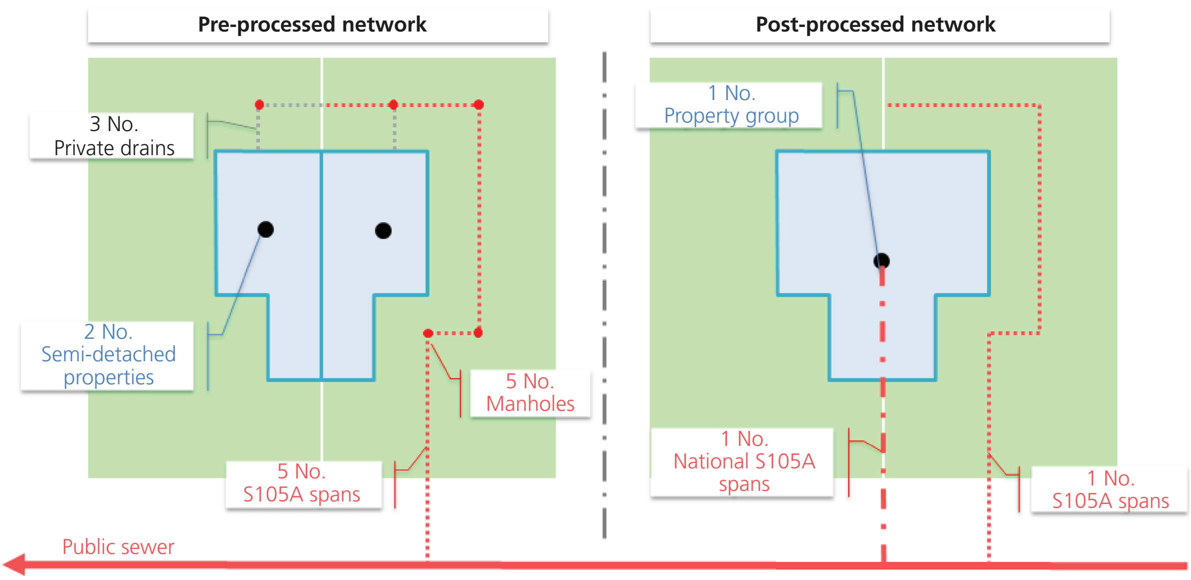

Figure 2. Pre- and post-network processing models

Property type	Age band	Function	Sewer length (observed)		Coefficient	
			Mean: m	Upper 95 percentile: m	Mean	Standard deviation
Detached	1937–69	Surface water	24·0	67·2	0·39	0·020
		Foul/combined	18·4	57·3	0·63	0·271
	1970–99	Surface water	15·3	43·1	0·71	0·179
		Foul/combined	11·5	33·0	0·80	0·022
	>1999	Surface water	11·5	29·3	0·75	0·213
		Foul/combined	9·4	26·4	0·93	0·165
Semi-detached	1937–69	Surface water	20·8	59·6	0·68	0·172
		Foul/combined	13·7	40·5	0·70	0·324
	1970–99	Surface water	14·1	39·4	1·03	0·027
		Foul/combined	10·5	29·9	0·86	0·937
	>1999	Surface water	10·5	25·6	1·12	0·156
		Foul/combined	8·3	23·5	1·36	0·226
Terrace	1937–69	Surface water	20·0	54·5	1·39	0·627
		Foul/combined	13·2	40·7	1·52	0·999
	1970–99	Surface water	15·1	39·8	1·71	0·204
		Foul/combined	8·8	26·0	2·19	0·715
	>1999	Surface water	10·9	27·0	1·83	0·364
		Foul/combined	7·6	22·7	2·48	0·298

Table 1. S105A length and calibration factor properties

Given the uncertainty surrounding the calibration factors, a Monte Carlo simulation was run using each coefficient's mean and standard deviation values (Table 1) to understand the statistical properties of the output when a probability distribution is assigned to the input factors, whereby the output forms the estimate of private sewer length and the inputs are the individual coefficients.

Figure 3 displays the output from the Monte Carlo simulation as a probability density for the overall foul-combined S105A sewer network length in South West Water's region, thus predicting the network to be between 4130 and 4809 km at a 90% confidence interval. The same output is produced for the S105A surface water sewer network to form an overall estimate of the transferred sewer length. The output is therefore a more comprehensive understanding of the S105A network length, which can be visualised graphically to help understand uncertainty.

Modelling deterioration and collapse risk for S105A assets

Due to the challenges associated with the largely unmapped and unattributed nature of the transferred private sewer network, the segregation of assets into cohorts is even more challenging and uncertain. A three-stage process was followed: (1) a literature study is conducted to identify the factors influencing pipe deterioration; (2) a review of the possible sewer attribution available is compared against the influencing sewer characteristics identified; and (3) the availability of historic condition information across the public and S105A network is collated, analysed and understood. This process ensures the selection of cohorts that form sufficient groups that are small enough to be uniform and meaningful in the way that they behave while retaining a significant population to yield meaningful results and reduce the influence of noise (Kleiner and Rajani, 1999).

In terms of influencing sewer characteristics, Davies *et al.* (2001) provide a comprehensive review of rigid sewer characteristics that commonly influence the deterioration of these assets. The deterioration model presented in this paper uses age, diameter, material and soil type to portion the sewer network into unique cohorts for the following reasons. Age was selected as a portioning attribute because it is commonly regarded as an influential factor in pipe deterioration. This can be as a result of more defects being observed on older pipes (O'Reilly *et al.*, 1989) or because of particular age bands causing more problems than others, for example, 1940s to 1950s (Lester and Farrar, 1979). However, determining and attributing sewer installation dates retrospectively cannot be precise and in general a date range is used in conjunction with an assumed discrete probability distribution. Therefore, a logical data hierarchical procedure was developed to take advantage of the most appropriate data sources. The process used a mixture of corporate sewer asset age data, property age estimates from the HM Revenue and Customs (HMRC) Valuation Office Agency and historic mapping, depending on data availability.

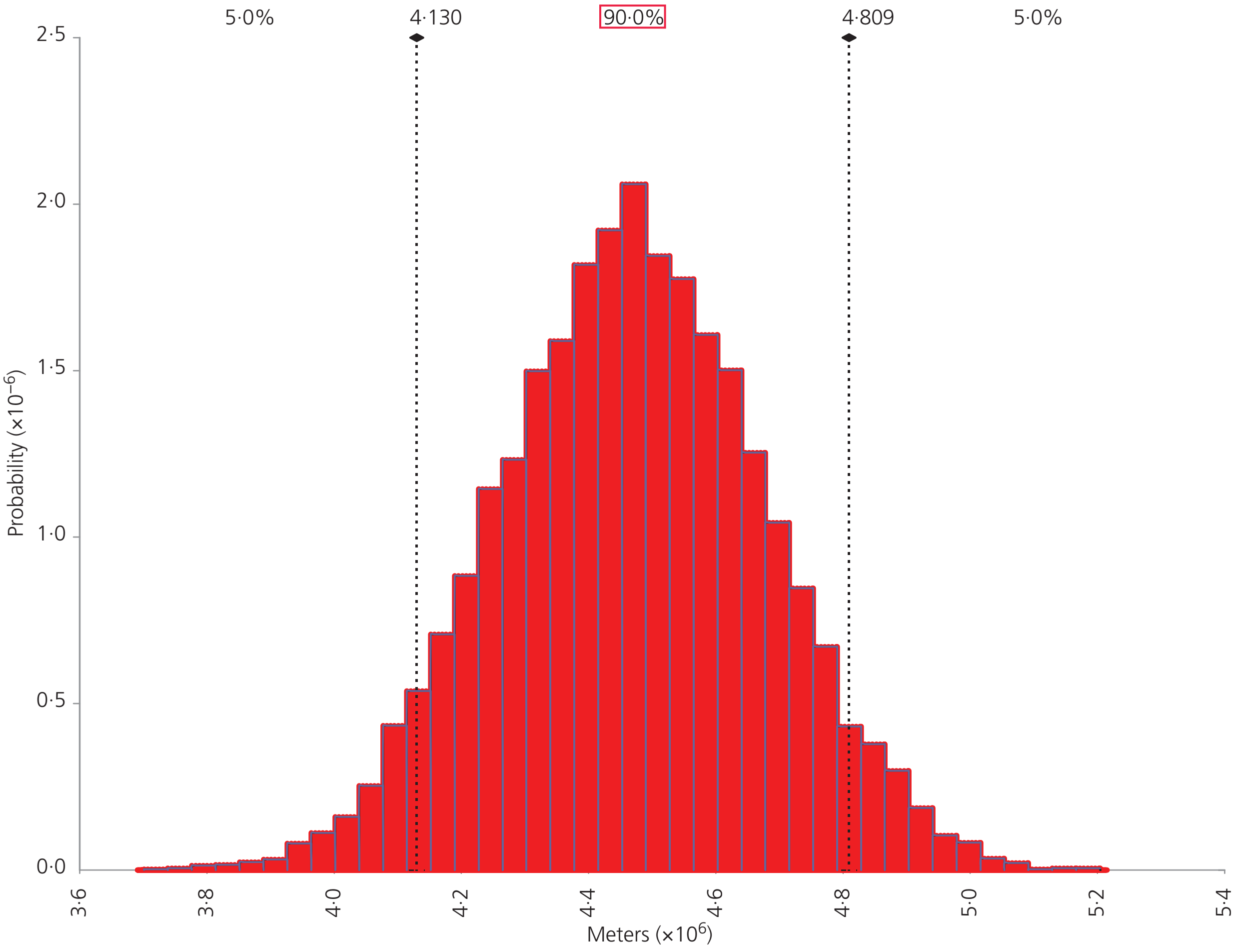

Figure 3. Total S105A foul-combined length distribution

Diameter is a widely attributed characteristic that also accounts for the differences between public and S105A sewers, whereby the former are more often of larger diameter. Ariaratnam *et al.* (2001) identified the statistically significant relationship between sewer diameter and failure rates in a logistic regression model that was applied in a study conducted in Edmonton, Canada. The material of the sewer was also considered in this model and deemed a significant factor influencing the rate of deterioration. In the public sewer network, material is often well attributed. However, in order to estimate the likely material of S105A assets, a rule set was solicited from a compilation of operational staff knowledge across South West Water. It can be seen that in some installation years more than one pipe material was in common usage. Table 2 therefore expresses the percentage likelihood of an asset being of a certain material based on its installation year. These percentages are applied to the individual assets so that a single sewer installed in 1967 would have its length proportioned across clay and pitch fibre at the appropriate ratios shown in Table 2.

Age band	Likelihood of separate surface water sewer: %	Material and (Code)		
		Clay (4): %	Pitch fibre (5): %	Plastic (6): %
1937–1969	25	74·84	25·16	0·0
1970–1999	60	67·0	0·0	33·0
>1999	90	10·0	0·0	90·0

Table 2. S105A age bands, surface water arrangements and material probabilities

Soil type is the fourth and final portioning factor. A statistical evaluation of public sewer collapse events against soil type was completed using the National Soil Map of England and Wales vector and the soil risk mapping purchased from the National Soil Resources Institute (NSRI, 2013). This identified statistically significant differences between different groupings of soils, which were ranked into four collapse risk bands ranging from none to high risk. From a geotechnical engineering perspective, the outputs were logical, whereby sewers in soils with low cohesivity (i.e. sandy, silty soils) and that allow free movement of water were found to be more likely to collapse than those soils with high cohesivity (e.g. clay). Other attributes, including depth, workmanship, overland use, ground disturbance and ground water level, have been disregarded for some, or all, of the following reasons: (*i*) the attribute is sparsely populated and difficult to infer for newly transferred private sewers with any reasonable level of accuracy; (*ii*) the attribute is less influential to the sewers' performance; and/or (*iii*) inclusion of the particular attribute would not retain a statistically significant set of cohorts.

In order to define, evaluate and forecast the probability of sewer collapse, a unique sewer deterioration model was established to predict the future condition of the network. The model uses the analysis of historic CCTV survey information to identify unique deterioration trends for different cohorts of sewer. Extrapolation of these deterioration trends allows for the entire sewer network to be expressed in terms of its length within each of the appropriate condition grade scores (1 to 5) at any point in time, whereby the WRc (2004) Method of Sewer Condition Classification is used to define condition grade. Against this understanding of past, current and future condition, a collapse rate is predicted based on a statistical analysis of historic events against the observed sewer condition profiles for each cohort. The result is a novel relationship that is drawn between sewer collapse rate and sewer condition profile using a linear function that allows for the future prediction of collapse rate over time.

Sewer condition is uniquely expressed in this model as the length of each sewer within each of the five condition grades, which are derived by modelling the sewer gradual transition from grade 1 (as new) to 5 (defective or collapsed) using a semi-Markov chain. Semi-Markov chains are a long-established technique for the mathematical modelling of infrastructure deterioration (Kleiner, 2001; Li and Haims, 1992; Micevski *et al.*, 2002; Wirahadikusumah *et al.*, 1999). It is commonly referred to as a simplification of the deterioration process because the modelling is often performed at asset level, with a single sewer occupying only one of a number of states, for example, 1 to 5. A probability is then applied to each asset to account for the likelihood of the entire asset moving into another state over a given time period, for example, 1 year.

However, by adopting a condition profile-based approach, the authors have established a more representative modelling technique for sewerage assets that reflects the fact that a single sewer may be in multiple states at a single point in time (Micevski *et al.*, 2002). This is achieved through analysis of historic condition surveys to determine how the actual proportions of a sewer gradually flow into the five condition grades using a semi-Markov matrix. In essence, the condition 'profile' of a sewer is simply the proportion of its length within each condition grade (1 to 5), as shown in Figure 4. For this analysis, a condition 'profile' is computed for all available historic survey information using a bespoke algorithm. The algorithm progresses a 4 m-wide observation window along the length of the condition survey in 0·1 m intervals. Within each 0·1 m step, the condition grade derived from the aggregate defect scores is held against that length, and the associated lengths within each of the condition grades are then summed to derive the local peak score and divided by the total length of the survey to produce the profile.

This deterioration modelling process aligns itself with a similar methodology used for the statistical modelling of water distribution pipe failure and sewer failure respectively (Berardi *et al.*, 2008; Savic *et al.*, 2009). Both approaches group the entire network into fictitious pipes based on their attribution for which the relevant variables of the deterioration model are calculated using a length-weighted mean. In this instance, the condition surveys represent the pipes, and the proportion of the sewer occupying condition grades (1 to 5) represents the variables. When the proportions of the sewer in each of the conditions grades are grouped together, this is referred to as the sewer's condition profile. The condition profile can be calculated for an individual sewer or it can be used to express the overall condition of a group of pipes (cohort) using

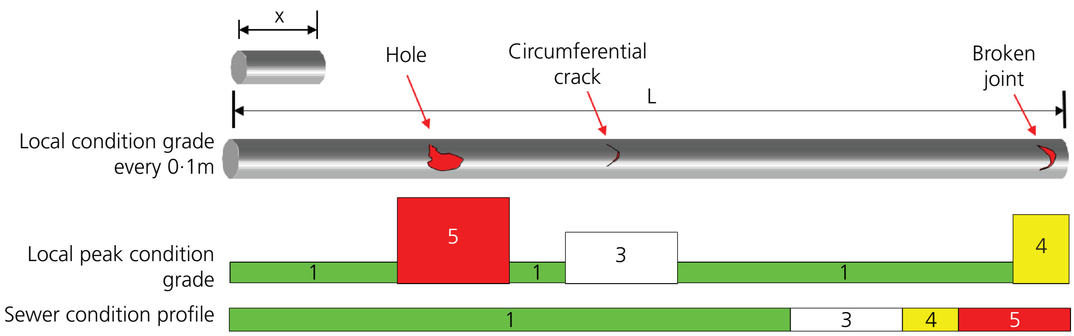

Figure 4. Sample sewer condition profile

the length-weighted mean approach. In this instance, the condition profile is calculated for all sewer cohorts, but only within a single survey year. The survey year is held as a segregating factor because it represents the age of the pipe at the time of the survey and is thus the time variable in the assets deterioration profile (Figure 5).

Once the survey and sewer attribution data are analysed, a semi-Markov deterioration matrix is calibrated against the observed sewer condition profiles on an annualised basis for each cohort of sewer. The resultant calibrated deterioration matrix, depicted in Table 3, can be interpreted as follows: The values in the leading diagonal of the matrix are the probable proportions retained in the same grade, for example, after 1 year it is probable that 98·7% of the length will remain in condition grade 2. The values directly below the leading diagonal refer to the probable proportions that will deteriorate to the next condition grade, for example, after 1 year it is probable that 1·3% of the length in sewer condition grade 2 will deteriorate to grade 3.

Using this annualised deterioration matrix to predict future condition, Figure 5 illustrates the comparison of the observed condition profiles (vertical bars) and the modelled estimate (linear trend). It can be seen that in some years the observed deterioration profiles are not particularly well aligned with the deterioration profile, that is, 2000. This reflects the fact that the model applies a weighting mechanism based on the length of survey information available in each year to either lessen or heighten the condition profiles' influence on the overall model calibration. This is witnessed by the two earlier observations in Figure 5, which represent only a small percentage of the overall survey length used in the model calibration and hence their seemingly insignificant influence. This approach provides for a more balanced and stabilised deterioration profile by smoothing the effects of small and potentially disruptive samples.

In the process of finding the optimal calibration factors for the model, the following constraints have been applied to the optimising routine. It is assumed that, in general, the collapse probabilities of lengths in grade 5 are greater than or equal to those in grade 4. Similarly, it is assumed that collapse probabilities of lengths in grade 4 are greater than or equal to those in grade 3. Finally, all of these values are constrained to be non-negative. Hence, the constraint $P_5 \geq P_4 \geq P_3 \geq 0$ has been applied.

Collapse rate calibration from historic failures

Semi-Markov deterioration modelling is a proven technique to simulate the gradually deteriorating profile of the sewerage network (Black *et al.*, 2005; Ruwanpura *et al.*, 2004; Scheidegger *et al.*, 2011). While it is important to predict and understand the length of sewerage assets across the network in each of the condition grades

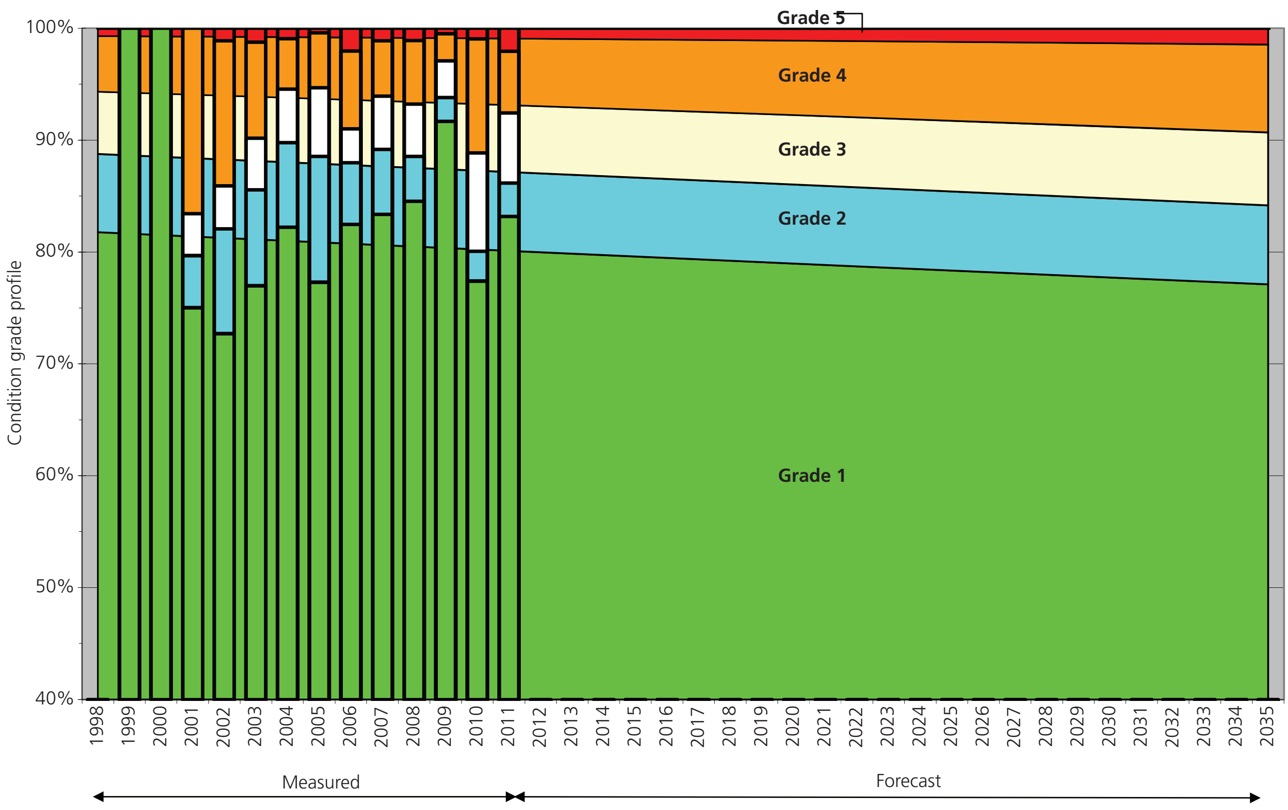

Figure 5. Example showing measured and forecast sewer condition profiles

		From grade				
		1	2	3	4	5
To grade	1	**99·8%**	0·0%	0·0%	0·0%	0·0%
	2	*0·2%*	**98·7%**	0·0%	0·0%	0·0%
	3	0·0%	*1·3%*	**97·3%**	0·0%	0·0%
	4	0·0%	0·0%	*2·7%*	**99·6%**	0·0%
	5	0·0%	0·0%	0·0%	*0·4%*	**100·0%**
		100·0%	100·0%	100·0%	100·0%	100·0%

Table 3. Example of a calibrated semi-Markov deterioration matrix

(1 to 5), the condition grade alone provides little information about the actual performance of the network in a reportable metric, such as collapse frequency. For example, a sewer of a particular material may remain in condition grade 5 without resulting in a reportable sewer collapse or experiencing any serviceability problems for a number of years. Whereas a sewer constructed in a more fragile material may experience more rapid deterioration, and therefore its collapse would be imminent.

In an attempt to overcome this challenge, the authors uniquely model sewer collapse rate as a function of the sewers' predicted condition profile. This is achieved using a linear equation that seeks to determine an overall sewer collapse rate (λ) for each cohort by calculating a series of coefficients (C_i) that are applied to the proportion of sewer length predicted to be in condition grades 3 to 5 (P_i). Therefore, as the pipe deteriorates over time and the proportion of sewer classified as condition grade 3 to 5 increases, then the predicted sewer collapse rate will also increase proportionally, following the relationship presented mathematically below

$$\lambda = \left[L \times \sum_{i=3}^{5} (C_i \cdot P_i) \right] + C_c$$

where λ is the sewer collapse rate (number/year), L is the total sewer length by cohort (km), C_i is the coefficient by condition grade (nr/km/year), P_i is the proportion of sewer length in respective condition grade (%) and C_c is a constant coefficient to account for third party incidents (nr/km/year).

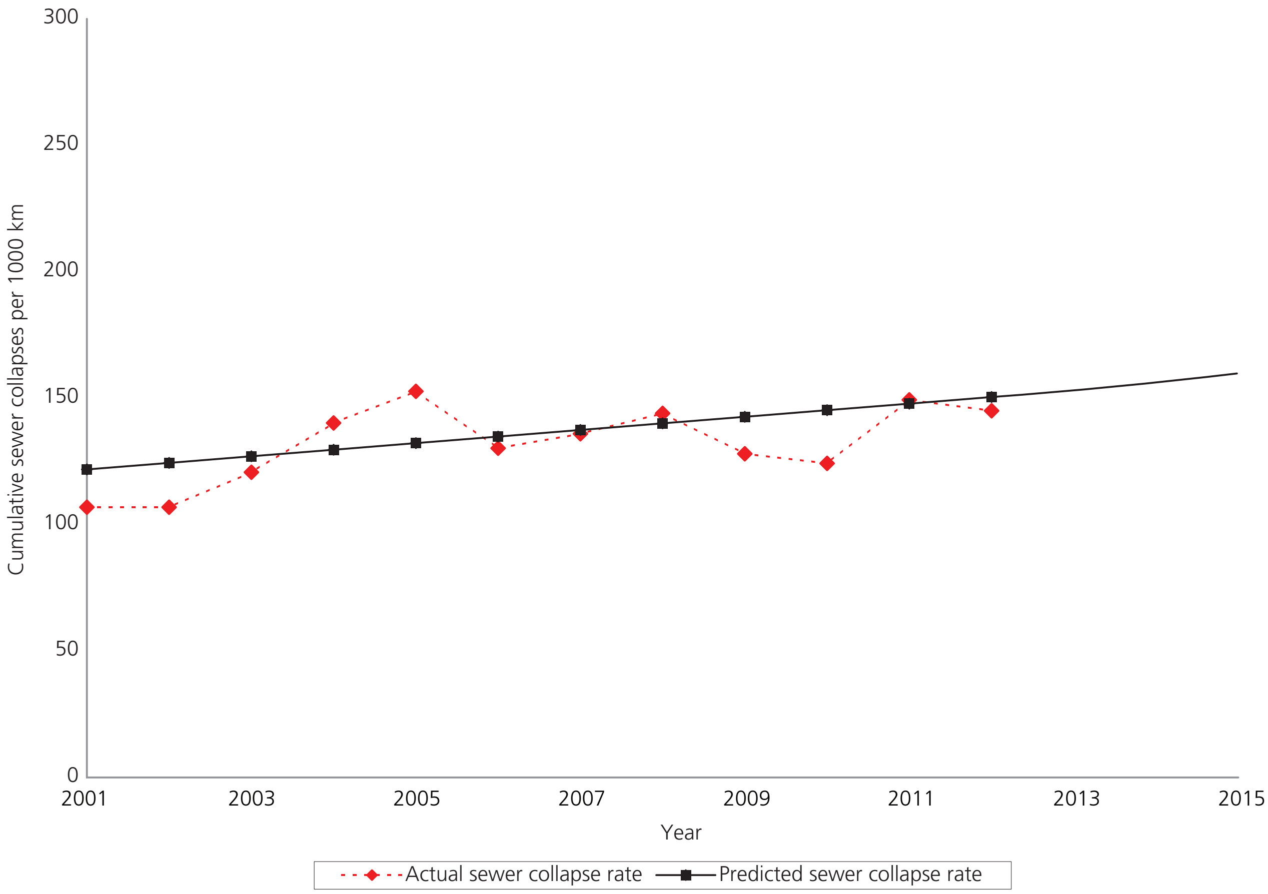

Figure 6. Cumulative reported and forecast collapses for Pitch fibre (1980–1989)

The coefficients in this expression are determined by minimising the error between the observed sewer collapse rate and the predicted collapse rate (λ) for each cohort, thereby accounting for the differing rates of collapse for each material. The process uses the historic sewer collapse rate for each cohort as a known entity that can be expressed as a cumulative count per calendar year over time (Figure 6). Similarly, the proportion of sewer (P_i), in condition grades 3 to 5, is derived using the previously described sewer deterioration modelling techniques, and it can also be expressed over time (see Figure 5). From this position, an optimisation routine is applied to minimise the error between the predicted and observed collapse rates by adjusting the coefficients in the expression (C_3, C_4, C_5 and C_c), which are the only unknowns in the equation. It is then assumed that these calibrated coefficients remain constant over time, so that when they are applied to a deteriorating sewer condition profile the collapse rate will increase proportionately.

The output from the model is a predicted sewer collapse rate (λ) for each cohort, expressed as a count per 1000 km/year, at any given year into the future. Therefore, the cumulative length of sewer across the network in each cohort can be multiplied by the collapse rate to obtain the number of predicted collapses in that year.

In light of the fact that S105A sewer collapses are largely unregistered, due to the transfer in ownership happening very recently, the collapse events witnessed on the public sewer network have been used as proxy in the model calibration process for cohorts of S105A sewers with the same attribution as their public sewer counterparts. The outputs from this deterioration and collapse modelling process can also be expressed as a collapse frequency for each cohort of sewer over time, thereby indicating the most vulnerable sewer cohorts and the rate at which their collapse frequency increases (Figure 7).

The relevance of using the window of public sewer condition and collapse information to inform a deterioration model for the newly transferred S105A network has been proven statistically by testing the following null hypothesis: 'sewers with the same fundamental characteristics (age, material, diameter, soil) will behave the same regardless of their acquisition status, that is, Public or S105A.' The validation process was conducted by comparing a random sample of the mapped S105A network, which was obtained solely for this purpose, against the historic survey information used in the deterioration modelling phase for the public network. The random samples across the S105A network were translated into condition profiles following the same modelling principles as the public sewer network, as described previously. A statistical test using analysis of variance (Anova) was then carried out on the estimated collapse rates for each cohort where sufficient sample sizes existed for both datasets. This test was set up to refute the null

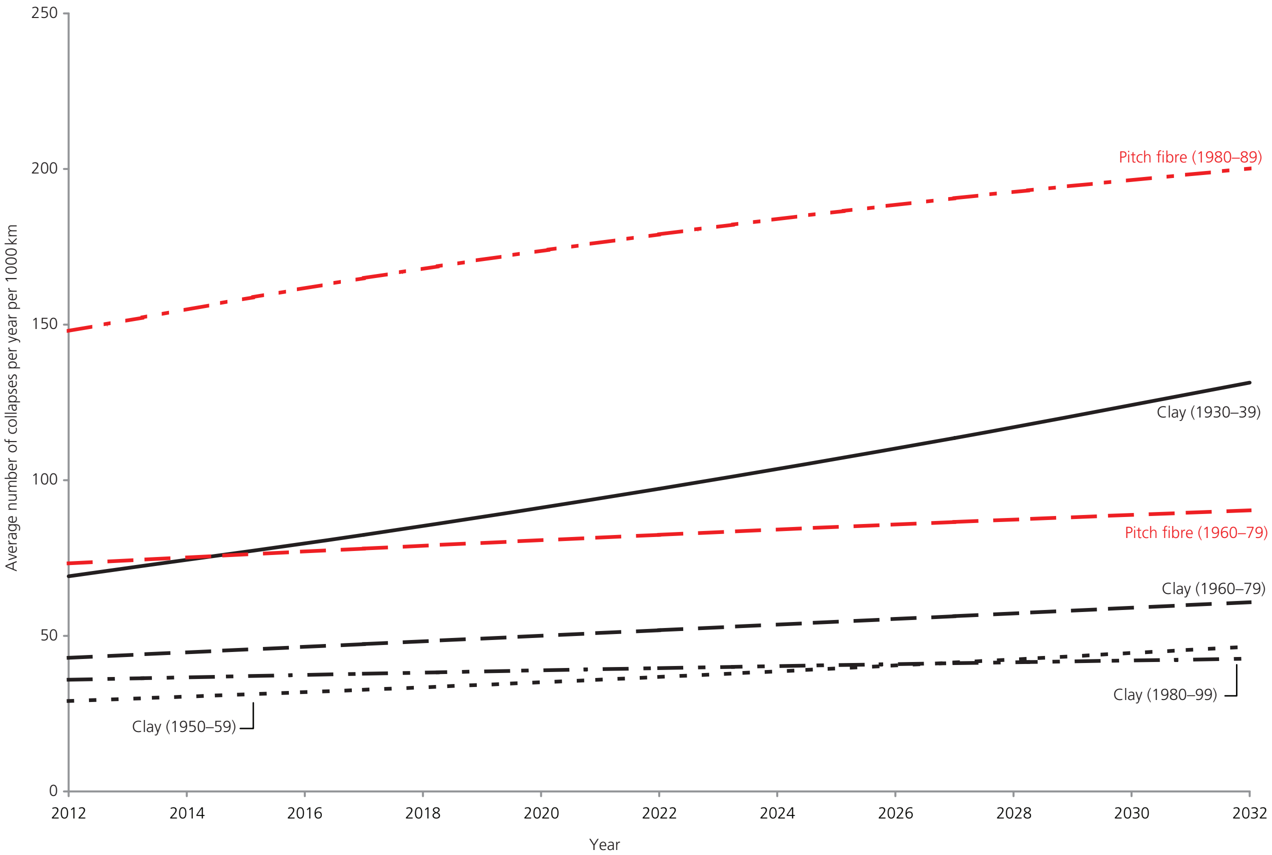

Figure 7. Sample sewer collapse frequencies

Ref	Sewer cohort			Sample size (Nr.)		Anova
	Installation date	Material	Size: mm	Public	S105A	P-value
1	1930–1939	Clay	≤165	154	12	0·301
2	1950–1959	Clay	≤165	709	25	$2{\cdot}24 \times 10^{-23}$
3	1960–1969	Clay	≤165	521	60	0·356
4	1960–1969	Pitch fibre	≤165	36	13	0·323
5	1970–1979	Clay	≤165	1778	16	0·883
6	1970–1979	Pitch fibre	≤165	110	45	0·123
7	1980–1989	Clay	≤165	451	35	0·437
8	1980–1989	Pitch fibre	≤165	76	69	0·088
9	1990–1999	Clay	≤165	1884	11	0·607

Table 4. Anova test for public and private sewer deterioration rates

hypothesis that the two sets behave in a similar manner in terms of their deterioration and failure due to collapse. For the purpose of validating the two datasets, an age band resolution of 10 years has been applied (Table 4).

Out of the nine sample cohorts tested, which are representative of approximately 72% of the entire S105A network, eight of these had little or no evidence at the 99% confidence level to reject the assumption. While only one cohort, 1950–1959 clay sewers less than 165 mm in diameter, represents less than 8% of the network rejected the assumption. This result provides a sufficient degree of confidence in the use of the public sewer deterioration model for the analysis of the S105A network.

Conclusions

A series of innovative tools to help formulate a proactive asset management strategy for recently transferred private sewers have been presented. The methodology is founded on an enhanced bottom-up assessment of asset stock, which is provided to the user within windows of uncertainty. The approach is structured to work with readily available datasets and is capable of applying innovative geospatial processes at individual property level to vastly enhance the level of information available. A sewer deterioration model is then applied against this improved asset stock to predict the underlying performance of the network in terms of its collapse rate now and into the future.

The model is calibrated using a 10-year window of public sewer condition and collapse records, which has enabled it to effectively differentiate between the poorly performing cohorts of sewer and those that are more stable. For example, in 2017, vitrified clay sewers laid between 1950 and 1959 have a predicted collapse rate of 32 (collapses per 1000 km/year), whereas pitch fibre sewers laid between 1980 and 1989 are predicted to be more problematic with a collapse rate in excess of 164 (collapses per 1000 km/year). Following the application of the public sewer deterioration model to the S105A network, the location, extent, age, material and predicted condition of the entire S105A network are better understood. This provides the foundations to estimate the likely investment requirements in the network going forward while also providing the basis for a proactive asset management strategy to be established by targeting survey investigations by way of CCTV toward poorly performing asset groups.

This methodology is mutually beneficial from both a business planning and a proactive asset management perspective. For business planning, the model develops a comprehensive understanding of the transferred sewer network, which for most water utilities remains an area of uncertainty. It also provides an improved understanding of the likely future performance of the transferred sewer network, which has allowed South West Water to develop a more robust business planning submission to the Office of Water Services (Ofwat), the economic regulator for England and Wales. For proactive asset management, the methodology provides a mechanism for South West Water to effectively guide their proactive rehabilitation programme toward poorly performing sewers, thereby reducing time and survey costs for the business while also ensuring that sewers with a high risk of failure are repaired first.

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