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REPORT

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D 1.2 REVIEW OF SEWER DETERIORATION MODELS

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by

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Abstract

The adoption of decision support tools for the definition of cost-effective strategies is seen to gain more importance in the coming years. This development is due for one part to the general degradation of the existing systems and for the other part to changes into the regulations and demands for more transparency in decision-making (Ana and Bauwens, 2007). A key element of decision support systems is the ability to assess and predict the remaining life of the assets (Marlow *et al*., 2009). For this purpose, deterioration models have been developed to understand and describe the sewer aging based on available CCTV inspections and a list of factors that influence the deterioration.

This report first describes the potential sewer deterioration factors and analyzes a panel of literature case studies regarding the relevance of each factor on sewer deterioration. Results are hardly directly comparable, because of the different construction practices, historical backgrounds and environmental conditions of the networks investigated. However, some trends regarding the most significant factors may be identified. In most studies, the construction year and the material seem to be the most relevant factor to explain sewer aging. Pipe size, depth, location and sewer function show generally a medium significance on sewer deterioration. Pipe slope was found to have a low significance for the structural deterioration, but a high relevance on the hydraulic deterioration. The effect of other factors as pipe shape, pipe length, soil type, sewer bedding, presence of trees, installation method, standard of workmanship, joint type, and ground water level have been highlighted but rarely or never investigated.

On a second step, this report presents three main approaches for sewer deterioration modeling: deterministic, statistical and artificial intelligence based models. The models can be further categorized into pipe group and pipe level models (Ana and Bauwens, 2010). Pipe group models (e.g. Cohort survival or Markov) can be used to predict the condition of a group of sewers or cohorts and are useful to support strategic asset management, i.e. the definition of long term strategies and budget requirements. These models enable to evaluate the efficiency of several scenarios at the network scale. Pipe level models (e.g. regression, discriminant analysis, neural networks) can be used to simulate the condition of each single pipe. They may be useful to set priorities and justify asset management operations. Pipe level models are tools that can support the utilities in the short and mid-term planning and determine at a finer resolution how, when, and where to rehabilitate sewers.

Literature results indicate that cohort survival and Markov models are two useful approaches for modeling the degradation of pipe groups. However, the quality of prediction of these models depends highly on the availability of a large amount of inspection data. Extensive datasets are required to create representative sewer groups (cohorts) with sufficient inspected sewers in each condition state. Regression and Discriminant Analysis were tested on several case studies but showed pretty low prediction performances. Three main reasons could be (i) the non-validity of model assumptions, (ii) the biased distribution of the datasets in terms of number of samples for each condition state and (iii) the lack of data for important deterioration factors. Neural networks have proven to be successful tools for the prediction of the deterioration of individual pipes. However, they require (i) relatively complex and time-consuming training processes and (ii) extensive datasets of CCTV inspection and deterioration factors.

Only very few case studies intended to evaluate the quality of prediction of these deterioration models. Furthermore, validation results are often contradictory and hardly comparable since (i) the data available for model calibration differ (percentage of CCTV available, type of deterioration factors available) and (ii) the metrics of the methodologies used to assess the quality of prediction differ. Thus, there is still no clear conclusion about the best modeling approach depending on the modeling purpose (pipe group or

pipe level). There is also no clear conclusion regarding the quality of prediction that can be reached since in most case studies only a few percentages of CCTV data were available and many data regarding potential deterioration factors were missing. Further research work is needed in order to

- Identify the most appropriate modeling approach depending on the modeling purpose
- Understand the influence of CCTV data availability on the modeling results
- Analyze the influence of input data uncertainty (CCTV and deterioration factors) on the modeling processes
- Find out the optimum input data requirement (availability of CCTV data and deterioration factors) for model calibration.

Table of Contents

Introduction

Asset management is an increasing concern for wastewater utilities and municipalities. Recent infrastructure studies underline the general deterioration of sewer systems and the risk reversing public health, environment and increasing costs (ASCE, 2009). Aging pipes have not been inspected, replaced or rehabilitated rapidly enough to prevent sewer deterioration and increasing system failures (Tuccillo *et al*., 2010). In the last 30 years, most municipalities have invested in sewer system expansion and treatment plant upgrade but a relatively small component has been allocated to the improvement of sewer system conditions.

Only a part of the funds needed to upgrade the condition of sewer systems will be generated through increases of municipal taxes and user fees (Allouche *et al.*, 2002). Another strong effort will be required for the reduction of overall costs, through the use of decision support systems for the definition of cost-effective rehabilitation plans and the optimization of inspection and maintenance programs. A key element of decision support systems is the ability to assess and predict the remaining life of the assets (Marlow *et al*., 2009). For this purpose, deterioration models have been developed by research and water utilities

(i) to simulate the actual condition of non-inspected (or non-recently inspected) sewers. The actual condition of the entire sewer network can be predicted, although only condition data about a part of the sewer network are available.

(ii) to forecast the future degradation of the network (Figure 1).

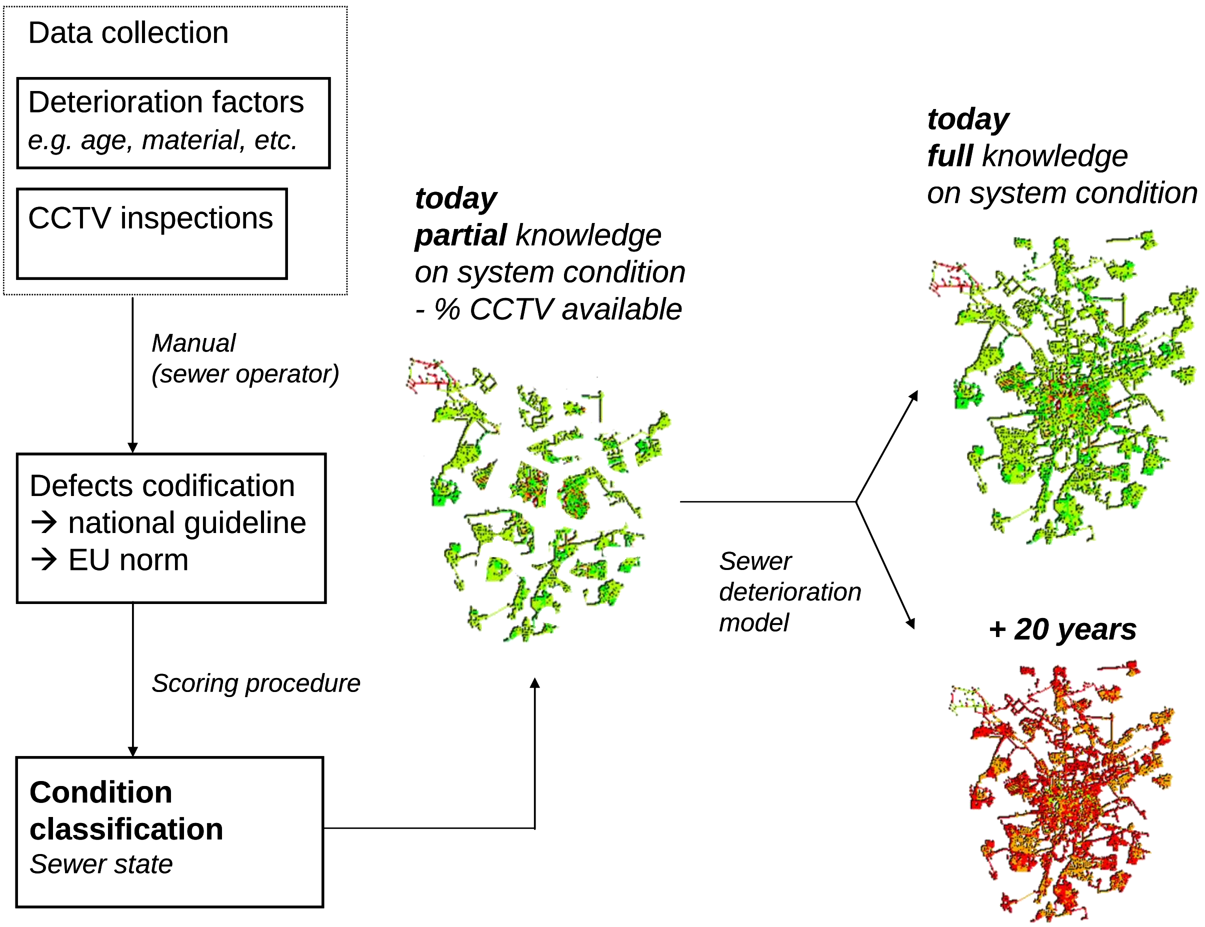

Figure 1: From CCTV inspection programs to sewer deterioration modeling. The condition evaluation of the available CCTV reports gives only a partial knowledge about the system condition. These condition data are used as input data to calibrate deterioration models and perform new predictions.

Input data to deterioration models are generally sewer condition data (condition evaluation from CCTV reports) and additional information about so-called deterioration factors that influence sewer degradation (pipe construction, operational and environmental factors).

Modeling results can be useful (i) to support the definition of long term strategies and assess budget requirements or (ii) to determine at a finer resolution how, when, and where to rehabilitate sewers.

Several modeling approaches are now available but not commonly used by sewer operators and municipalities to support strategies. Indeed, their ability to model sewer deterioration with an acceptable accuracy is still to be demonstrated. This step is crucial for the further development of deterioration models since their acceptance among water utilities depends mainly on the availability of proof of reliable forecasts (Ana and Bauwens, 2010). Since decision makers may use information from model results to plan or justify public investments, they are highly concerned by the accuracy of the model predictions (Sargent, 1999). Thus, the validation of deterioration models is still a primary task to be done in order to (i) build the confidence of end-users (utilities, municipalities) regarding models use and (ii) demonstrate the benefits of using modeling approaches to set asset management strategies.

This report first describes the list of potential sewer deterioration factors and analyzes several literature case studies regarding the relevance of each factor on sewer deterioration (Chapter 1). On a second step, three main approaches to sewer deterioration modeling are introduced: deterministic models, statistical models and artificial intelligence based models (Chapter 2.1). Lastly, this report summarizes available results concerning the application of deterioration models on full scale case studies regarding their reliability and the quality of prediction (Chapter 2.2).

Chapter 1 Survey of factors affecting sewer deterioration

The deterioration process of sewers can be divided into structural deterioration and hydraulic deterioration (WRc, 1986). The structural deterioration is characterized by structural defects (e.g. cracks, fractures) that may lead to structural failure such as a pipe collapse (Tran, 2007). The hydraulic deterioration is observed through hydraulic defects (e.g. intrusion of tree roots and deposits) that reduce the transport capacity and may lead to hydraulic failures such as blockage and overflow. A defect can have consequences on both structural and hydraulic degradation (e.g. intrusion of tree roots). In addition, the overall structural condition directly affects the sewer flow capacity since structurally deteriorated pipes with cracks and breaks have a rougher inner surface that increases the risk of debris accumulation (Chughtai and Zayed, 2008).

Generally, pipes deteriorate with age; however, deterioration rates can vary significantly between pipes depending on pipe construction, operational and environmental factors. Therefore, an older pipe will not necessarily be in a worse state than a newer pipe.

Since numerous factors affect the sewer deterioration, it is obvious that pipes of different types and characteristics have different deterioration behaviors. Therefore, these factors are considered as variables or covariates in the development and calibration of sewer deterioration models (Chapter 2). The deterioration factors are not used to explain the causes of deterioration but rather to find correlations with sewer deterioration and identify the circumstances in which a rapid degradation may occur.

A large number of potential deterioration factors have been presented in the literature (Davies *et al*., 2001). They can be divided in three groups:

- Pipe construction factors: e.g. pipe characteristics (age, material, etc.) and further construction factors (sewer depth, sewer bedding, etc.).
- Operational factors: e.g. sewer maintenance practices.
- Environmental factors: e.g. ground water level, surface load, soil and backfill type.

If data regarding pipe construction factors are typically available in the operators databases (e.g. material, age, etc.), operational and environmental factors are often missing. Some data are rarely collected by sewer operators since they are not directly related to their operational activity (e.g. surface load and traffic). On the other hand, some data (e.g. traffic intensity or soil type) may be already available at other municipal services (e.g. urban planning or road construction).

The identification of the most important influencing factors is primary for following reasons:

- to decrease the number of factors required to calibrate deterioration models. Due to the high costs associated with data collection, the comprehensive collection of data regarding all potential deterioration factors is not cost effective. Correlation between factors can reduce the number of explanatory variables to consider for model calibration. The same quality of prediction can be reached using less input data and thus reducing data collection costs.
- to ensure the reliability of the prediction of deterioration models. High prediction quality can be achieved only if data regarding most important deterioration factors are available.

Numerous authors analyzed the influence of deterioration factors on sewer condition (Ahmadi *et al.*, 2013; Ana, 2009; Baur and Herz, 2002; Chughtai and Zayed, 2008; Davies *et al*., 2001; Müller, 2006; O'Reilly *et al*., 1989; Tran, 2007). Table 1 summarizes the findings of different case studies that investigated the influence of factors on sewer deterioration using statistical methods.

Table 1: Significance level of deterioration factors on sewer deterioration according to the presented case studies

Reference / **Factors**	**Structural deterioration**						**Hydraulic**
	Baur and Herz (2002)	Müller *et al*. (2002)	O'Reilly *et al*. (1989)	Chughtai and Zayed (2008)	Ana *et al*. (2008)	Tran (2007)	Tran (2007)
Location of the case study	Dresden, Germany	4 cities in Germany	Southern water Authority UK	Pierrefonds & Niagara Falls, Canada	Leuven, Belgium	City of Greater Dandenong, Australia	
Inspected sewer length	64 km 4.6 % of pipe pop.	500 km, 280 km, 100 km, 500 km	180 km	-	90 km 27% of pipe pop.	417 data points 2.2% of pipe population	
Construction year	High	High	High	-	Medium	Low	High
Material	Medium	Low	High	Medium	High	-	-
Pipe size	Medium	Medium	Medium	-	Low	High	High
Pipe shape	High	-	-	-	Low	-	-
Pipe depth	-	High	Medium	-	Low	Low	Unde-cided
Pipe length	-	-	-	-	High	-	-
Pipe slope	Medium	-	-	Low	Low	Low	High
Sewer bedding	-	-	-	High	-	-	-
Sewer function	Medium	High	Medium	-	-	-	-
Location/ Traffic	Low	Low	Medium	Medium	(Low)	High	High
Tree-count	-	-	-	-	-	Unde-cided	Low
Soil type	-	High	High	-	-	Unde-cided	Unde-cided

The influence of only few factors has been evaluated in the case studies depending on the data available in the operator databases. Furthermore, results are hardly directly comparable, because of the different construction practices, local conditions and data availability. However, some trends regarding the most significant factors may be identified.

- The **construction year** has generally a very high influence on the structural and hydraulic deterioration processes. It indicates the sewer age and represents the historical background of the investigated area (e.g. standard of workmanship, material quality).
- The types of **sewer material** (concrete, clay, etc.) differ in each case study, but have generally a high relevance on sewer deterioration (Baur and Herz, 2002; Müller and Dohmann, 2002; Ana *et al*., 2008).

- **Pipe size**, **depth**, **sewer function** and **location of the pipe** show a medium significance on sewer deterioration. These factors can be easily considered in deterioration modeling since data are usually available.
- **Pipe slope** was found to have a low significance for the structural deterioration but a high relevance on the hydraulic deterioration.
- The effect of **pipe shape** and **length** was rarely investigated, although data of these factors are usually available. Further research is necessary to evaluate their influence on sewer deterioration.
- The factors **soil type, sewer bedding** and **presence of trees** have been rarely investigated since few data are available in the network databases. Further studies are needed since they are often considered to have a major influence on structural and hydraulic deterioration.
- As far as we know, other potential significant factors, such as **installation method**, **standard of workmanship**, **joint type**, **and ground water level** have not been investigated quantitatively.

The next paragraphs present in detail the potential deterioration factors. The results of specific studies are shown in order to state the influence of different factors more precisely.

1.1 Description of factors influencing structural conditions

1.1.1 Pipe construction features

Construction period and age

The construction year affects the sewer condition since it represents the sewer age and the quality of the construction work. Since the origin of sewer systems in the 19th century, sewers have been installed at different periods using available standards and technologies. The state of the art of sewer construction and the economic situation (e.g. years of war, economic crisis, high construction activities) affects the quality of construction work and material used.

Müller and Dohmann (2002) pointed out that the defect density is particularly high for sewer pipes constructed during the Second World War in Germany due to the lack of qualified personnel. According to Baur and Herz (2002), pipes constructed during socialist periods in East Germany have higher rehabilitation needs due to the use of poor material quality and insufficient bedding conditions. Furthermore, the quality of construction work may decrease during periods of intensive construction activity. Davies *et al*. (2001) identifies that sewer pipes constructed between 1918 and 1939 (interwar period) in the UK have the highest defect density and pipes constructed from 25 years after the Second World War forward have a decreased deterioration rate due to the use of improved technologies.

Pipe Material

Material types used in the construction of sewer pipes affect their reaction to the environmental factors (Salman, 2010). The distribution of main sewer material differs between countries and cities.

Concrete pipes are commonly in use for sewer pipes due to their high abrasion resistance, strength and cost (Ana, 2009). Davies *et al*. (2001) state that the primary cause of concrete sewer failure is the corrosive action of hydrogen sulphide. Sulphide-reducing bacteria reduce sulphates contained in sewage under anaerobic conditions and form dissolved hydrogen sulphide (H_2S). When H_2S is being oxidised to sulphuric acid (H_2SO_4), it may attack alkaline materials like concrete surfaces and asbestos cement.

Clay pipes are highly resistant to acids and are therefore suitable for sanitary pipes with high acid concentration. Disadvantages of clay pipes are their restriction to circular shapes, their limited pipe length and their brittleness so they are prone to fractures (Ana, 2009).

Plastic pipes, like PVC pipes, are chemically inert to acidic and alkaline wastes and have watertight joints. However, PVC pipes can undergo excessive deformations under loading, especially when installed improperly or when transporting high temperature wastes.

Ana (2009) found out that concrete pipes are more durable than brick pipes. O´Reilly *et al*. (1989) investigated that vitrified clay pipes are found to be more deteriorated than concrete pipe since clay ware is the oldest pipe material used in the UK. Salman (2010) summarizes advantages and disadvantages of common material types like asbestos cement, cast iron, concrete, vitrified clay and plastic materials.

Pipe size

Literature results about the effect of pipe size on the deterioration process are contradictory. Davies *et al*. (2001) suggested that larger pipes have a lower risk of deterioration, because they are laid more carefully due to their bulk and weight. On the other hand, O'Reilly *et al*. (1989) analyzed 180 km sewer length and found that longitudinal cracks and fractures increase with diameter: small pipes (300 mm in diameter and smaller) have smaller moments of inertia and therefore are less resistant to bedding movements. Some studies prove the assumption of a decreased deterioration rate of small pipes (Ana *et al*., 2008; Baur and Herz, 2002; Müller and Dohmann, 2002).

Pipe shape

Only few studies investigated the deterioration behaviors of several pipe shapes (circular, egg shaped, U-shaped, box-shaped, etc.). Modica (2007) investigated the history of the sewer network of Newark (USA). He indicates that circular brick sewers show the highest structural performance. Baur and Herz (2002) investigated the sewer system in Dresden (Germany), which is mainly built of concrete and vitrified clay, and found out that egg shaped sewers deteriorated significantly slower compared to circular sewers.

Sewer depth

Several authors studied the influence of sewer depth on sewer condition state. (O'Reilly *et al*., 1989) describe that sewers have a decreasing defect rate up to 5.5 m below the ground level due to the decreasing influence of surface factors such as traffic. Shallow sewers at depth of less than 2 meters are significantly affected by the surface and therefore may have higher than average failure rates. Kawabata *et al*. (2003) also states that sewer pipes at a depth of 2 meters receive much lower earth pressures due to traffic loads than if pipes are laid in a depth of one meter. Furthermore, the effect of seasonal moisture variations in the soil surrounding shallow sewers may affect the deterioration process significantly (Davies *et al*., 2001). On the other hand, very deep sewers (below 5.5 m) are suggested to have an increasing defect rate with depth due to the increasing effect of soil pressure (Ana, 2009).

Sewer length

Ana *et al*. (2008) proves the assumption that long sewers typically deteriorate faster, because they have more areas of possible failure, like pipe joints. Furthermore, longer sewers have higher risk of settlement, which could increase blockages and corrosion.

Sewer slope

Flat slopes in sewers generally result in a low velocity of the transporting medium. The longer the wastewater stays in the sewer the more likely is the generation of hydrogen sulphide gas. Additionally, there is a higher risk of sediment deposition and clogging in sewers with flat slopes (Ana, 2009). On the contrary, pipes with steeper slopes may cause high flow velocity, which increases erosion and abrasion rates on the pipe lining (Chughtai and Zayed, 2008). Baur and Herz (2002) analyzed the deterioration rates of sewer with different gradients (<1%, 1-5%, >5%). Results showed that sewers with a medium slope (gradient or 1-5%) deteriorate slower than sewers with flat and steep slopes (gradients of <1% and >5%).

Installation method

Two different methods of installing and constructing sewers are available: trench and tunneling methods. Depending on the installation method, the soil-pipe interactions and the load resulting on the pipe differ. For example, the load and dynamic forces transmitted to the pipe can vary by as much as a factor of 10 depending on the width of the trench (narrow and wide), the pipe shape, size and sewer bedding material (Davies *et al*., 2001). Figure 2 shows an example of settlement due to the relative movement of the soil over the pipe. The bedding material is filled in the trench after installing the pipe. In general, the natural ground will settle slightly, the bedding material will compress and therefore the pipe will settle into its foundation until equilibrium is reached.

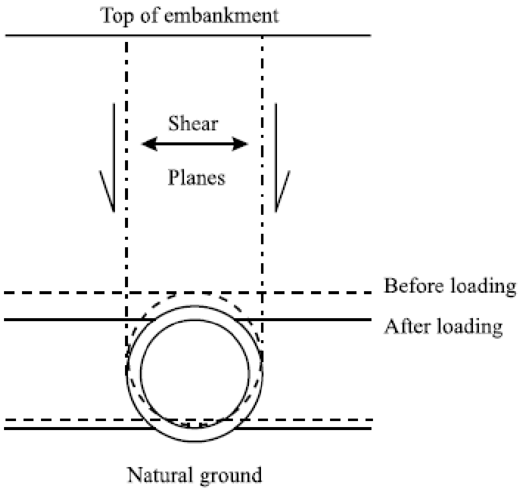

Figure 2: Settlement of bedding materials after the pipe installation according to the trench method (from Davies et al., 2001)

Trenchless tunneling methods are rather recent technologies so only a marginal amount of such sewers exist today. No study has been found that investigates the influence of the installation methods and characteristics on sewer deterioration.

Standard of workmanship

The standard of workmanship is often assumed to be a critical deterioration factor (Ana, 2009; Davies *et al*., 2001). Poor construction practices are considered to be the primary cause of sewer failures like structural defects and leakage at joints. It includes not removing rocks and tree roots from trenches, laying pipes to gradients other than design gradients, improper backfilling and consolidation and laying pipes sockets on bricks or blocks. Furthermore, construction methods can lead to the formation of voids around the pipe. For example, timbers left in trenches that decay with time and sub drains that have not been removed or adequately refilled after construction works lead to the formation of voids. The quantitative influence of the standard of workmanship has not been directly investigated in case studies. However, it may be assumed that it is related to the construction period and thus to the available standards and technologies.

Sewer bedding material

Sewer pipes require proper beddings as a structural support to ensure their long-time structural performance. The chance of pipe failure increases with improper bedding conditions. This includes the choice of the type of the bedding material as well as the proper installation (filling and compression). In the UK, the British Standard BS EN 1295-1 (1998) describes six bedding classes for rigid sewer pipes (D, N, F, B, S and A) with bedding class B – single size granular cradle type – as the most common used class in the UK (Davies *et al*., 2001). According to BS EN 1295-1 (1998), a bedding factor can be assigned to each bedding class. It determines the effectiveness of load and pressure distribution of the bedding materials around the pipe. Angular granular bedding materials were investigated to have a higher bedding factor than rounded granular due to their natural stability that resists displacements. In addition, the grain size has a high influence on the exfiltration rate, because larger particles allow a higher flow rate. Chughtai and Zayed (2008) compared the structural deterioration of concrete sewers in respect to the bedding class. They found out that concrete pipes deteriorate faster if they are laid in well-compacted backfill than in well-compacted granular material. This significant difference in the deterioration rate is suggested to be due to a higher vulnerability of displacements in weaker bedding materials.

Joint type and material

Sewer joins aim to ensure watertightness and resistance against root intrusions. Joint types have changed over the past 100 years due to technical development: from clay puddle (1880's) over lime and mortar (early 1900s) and cement mortar (mid 1900s) to flexible joints (1950s) (Ana, 2009). Flexible joints showed a degree of flexibility in line and level and their use is now almost universal. The watertightness of flexible joints is dependent of the stress within the joint ring. The stress must be distributed equally within the ring and therefore correct sized rings and a concentrically connection is essential (Davies *et al*., 2001).

1.1.2 Operational factors

Sewer function

Sewer pipes can be classified into sewers that transport sanitary only sewage, only stormwater or combined sewers that transport both. The quality of the wastewater transported through the pipe varies largely: from weak domestic sewage diluted with stormwater and groundwater infiltration, to chemically strong undiluted sewage from commercial establishments. Strong and aggressive sewage leads to material degradation such as internal corrosion and erosion. Internal corrosion is dependent on the sewage properties such as pH and sulphate concentration, whereas pipe erosion occurs with a high sewage flow velocity and presence of suspended solids (Tran, 2007). O'Reilly *et al*. (1989) found out higher defect rates for combined and stormwater sewers than for sanitary sewers. The explanation could be that combined and stormwater sewers are constructed shallower than sanitary sewers (increased surface loads) and have larger fluctuations in flow.

Sewer maintenance

Appropriate maintenance strategies, like sediment removal, sewer cleaning and root cutting, generally increase the service life of sewers. Nevertheless, cleaning techniques may accelerate sewer deterioration (Davies *et al*., 2001). For example, sewer-flushing techniques used to clean sewer sediments and clear blockages may cause damages to sewer materials due to high water pressures.

1.1.3 Environmental factors

Location: surface load and traffic

Land use and traffic above the sewer pipe affect the magnitude of surface loading carried to the pipe. Magnitude and frequency of surface loads vary in time and are difficult to measure or estimate. Loads may be classified into large one-time events (e.g. surface construction, in-ground utility construction, earthquakes, and landslide) and small cyclic events with hourly, daily or seasonal frequency (e.g. bus stops, traffic, maintenance activities) (Marlow *et al*., 2009).

The construction and structural design of new sewers require the consideration of estimated loads (BS EN 1295-1, 1998). Therefore, sewers under main roads may have higher construction standards and will not automatically deteriorate faster than sewers under light traffic roads although they have to carry greater loads. According to Müller and Dohmann (2002), the quality of construction work is rather the determining factor. Furthermore, loads transmitted to the pipe do not only depend on the traffic intensity, but also on other factors such as the structure of the pavement, the sewer depth and the pipe bedding.

O'Reilly *et al*. (1989) investigated the defect rates of sewers under different locations (different road types, field, garden, footpath and premises) and found out that sewer under roads with varying traffic intensities have a similar defect rates. However, sewers under gardens show a much higher defect rate than under roads, probably due to disturbance during houses construction works.

Ground water level

If the natural groundwater level lies above the pipe, groundwater may infiltrate through pipe defects. Water flowing through defects washes out soil particles and causes ground loss. This leads to soil density losses or to the formation of voids and therefore, to a lack of soil supporting the pipe (Davies *et al*., 2001). Roger (1986) investigated the effect of different groundwater levels on soil loss for various soil types.

Presence of trees

Roots of trees close to sewers may enter the pipes through defects (cracks, open joints or fissures) as they search for moisture. On the one hand, roots can open up and worsen the pipe defects, and on the other hand, the growth of roots inside the pipe affects the sewage transport. Further growth of roots inside the sewer exerts the pressure on the pipe that is sufficient to break the pipe (Ana, 2009). Tran (2007) analyzed the effect of tree-counts on sewer deterioration. The tree-counts were found to have a low to medium effect on structural deterioration. It is suggested that factors such as tree age, height and tree type may be more appropriate.

Soil type

The soil type may influence the risk of ground loss and the stability of the sewer. As described above, the loss of the surrounding soil occurs in the presence of water (groundwater, rainwater) in combination with pipe defects (e.g. cracks, fractures). The type of soil surrounding the sewer determines largely the degree of ground loss: fine, cohesionless soils such as silt and fine sand flow much faster with the water than coarse soils (e.g. gravel) and cohesive soils (e.g. clay) (Ana, 2009). Swelling of clay soils due to the change of water content in the soil imposes forces on the pipe structure. O'Reilly *et al*. (1989) showed that the sewer defect rate was the highest in clay grounds and the lowest in gravel soils. Besides, field studies on frost penetration found out that the expansion of soil due to freezing causes vertical forces on pipes (Davies *et al*., 2001).

1.2 Description of factors influencing hydraulic conditions

The factors presented above have a potential influence on the structural degradation of sewers. With a different magnitude, these factors can also affect the transport capacity of the pipes (hydraulic conditions). Some factors may have a low influence on the structural degradation of the pipes but a very strong effect on the hydraulic condition (e.g. presence of groundwater).

Hydraulic defects (e.g. deposits) primarily occur in sewers that do not have an adequate pipe size and pipe slope for the transportation of the sewage volume. Faulty design increases the risk of debris accumulation and blockage. Roots entering the pipe additionally affect the flow capacity and are a major factor of sewer pipe blockages (Chughtai and Zayed, 2008). The presence of trees and the soil type influence the risk of roots growing into the pipe. Furthermore, shallowly buried pipes (pipe depth) are more vulnerable to root intrusions, whereas deep sewers are rather affected by the groundwater.

The groundwater, as it flows through structural pipe defects, carries soil particles and salts that cause encrustations and debris (Tran, 2007).

The pipe location may also affect the type and the level of deposit build-up or debris accumulation. Depending on the location (e.g. road, park) and site characteristics (e.g. traffic volume, surfaces cover), the sources of natural and anthropogenic suspended solids vary significantly (Tran, 2007).

In addition to the deterioration factors, Chughtai and Zayed (2008) states that the overall structural condition directly affects the sewer flow capacity. Structurally deteriorated pipes with cracks and breaks have a rougher inner surface that increases the risk of debris accumulation.

Chapter 2 Sewer deterioration models

A wide variety of deterioration models has been proposed in the literature to predict the deterioration processes based on real-observed sewer conditions and deterioration factors. However, the models differ in i) the mathematical description of the deterioration process, ii) the data requirements and iii) the mode of calibration (Scheidegger *et al*., 2011). Existing sewer deterioration models can be classified into three basic groups: deterministic models, statistical models and artificial intelligence based models (Figure 3).

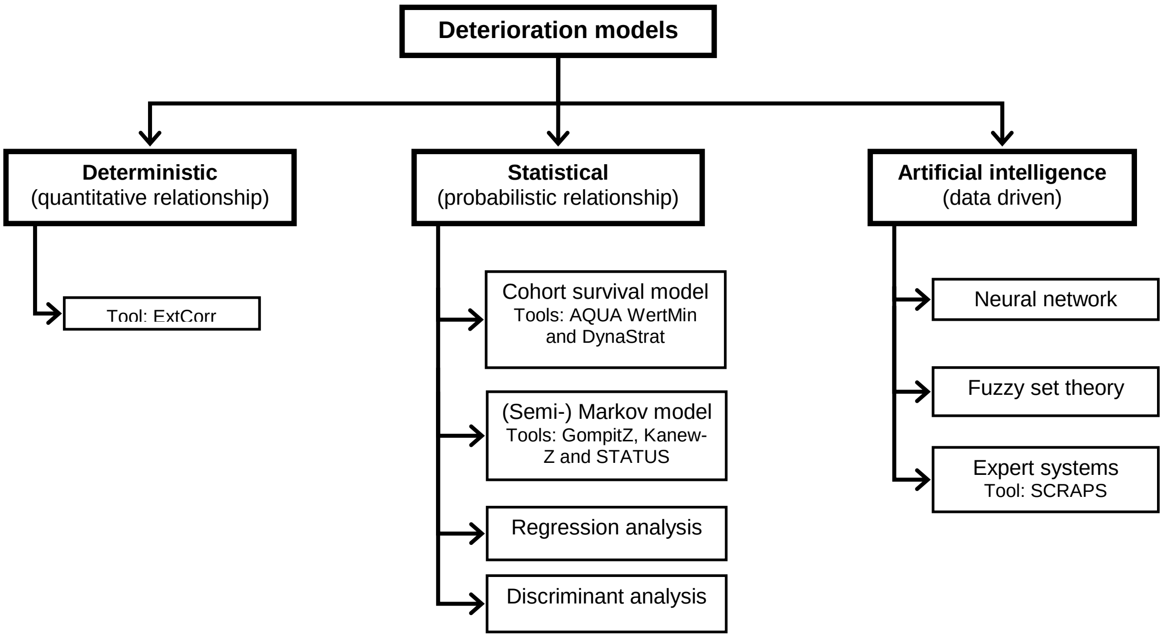

Figure 3: Overview of the different types of sewer deterioration models.

Deterministic models evaluate the quantitative relationship between deterioration factors and sewer condition using mathematical equations. They assume clear relations between deterioration factors and sewer condition and do not account for the uncertainty that is associated with asset deterioration and failure (Marlow *et al*., 2009). Statistical models take this uncertainty into account using probability based equations to relate deterioration factors to historical data of graded pipe conditions. Artificial intelligence based models are rather data-driven than model-driven. Neural Networks predict output from input information in a manner that simulates a simplification of the operation of the human central nervous system (Marlow *et al*., 2009). They investigate the mathematical relationships between predictors (independent variables, i.e. deterioration factors) and responses (dependent variables, i.e. discrete sewer condition classes) by “learning” the deterioration behavior of pipes from inspection data. Their structure is built based on the available sample data and is therefore considered as data-driven.

Sewer deterioration models can be further categorized into two main types of models: pipe group and pipe level models (Ana and Bauwens, 2010).

- Pipe group models can be used to predict the condition of a group of sewers or “cohorts” and are useful to support strategic asset management, i.e. the definition of long term strategies and budget requirements.

  These models enable the evaluation of the efficiency of several scenarios at the network scale.

- Pipe level models can be used to simulate the condition of each single pipe. They may be useful to set priorities and justify asset management operations and investments.

Pipe level models are tools that can support the utilities in the short or mid-term planning and determine at a finer resolution how, when, and where a sewer replacement is most reasonable. Pipe level models have the advantage that they can also be used at the pipe group level by creating groups of sewers.

Cohort survival models are pipe group models: the deterioration processes are described using homogenous sewer pipe groups (i.e. cohorts) sharing similar deterioration factors. They do not considerate deterioration factors as covariables. All other models are pipe level models and can also be used at the pipe group level. They consider the individual properties of pipes as covariates in predicting their individual deterioration (Ana and Bauwens, 2010).

This chapter presents the main approaches of deterioration modeling proposed in the literature and discusses the validation results of these models by comparing the findings of the few case studies concerning their reliability.

2.1 Type of sewer deterioration models

2.1.1 Deterministic models

Deterministic models are empirical or mechanistic models based on physical, chemical or engineering science knowledge of the phenomenon. Models were developed by understanding the physical mechanisms of sewer deterioration processes. Empirical deterministic models involve fitting some form of linear or non-linear equation to observations of asset failure (Marlow *et al*., 2009).

An example of deterministic model is ExtCorr developed within the Care-S project (König, 2005). The model estimates the external corrosion of concrete pipes by evaluating the soil aggressiveness, the soil moisture and the cement quality of the pipe.

Another example is the WATS model, a deterministic in-sewer process model for the simulation of internal corrosion. The model is based on the resolution of non-linear differential equations describing microbial and chemical transformation processes of organic matter, oxygen, oxidized nitrogen compounds, and sulfurous compounds (Vollersten and König, 2005).

Some single aspects, such as corrosion, can be modeled empirically, but the degradation of sewer condition remains a very complex process that is not completely understood and depends on a large amount of factors (Schmidt, 2009). Deterministic models are often too simplistic to reflect the actual deterioration process and the scarcity of data needed to simulate accurately the deterioration mechanisms decreases their applicability (Ana, 2009). They usually rely on a number of simplifying assumptions and do not account for the uncertainty that is associated with asset deterioration and failure (Marlow *et al*., 2009).

2.1.2 Statistical models

Statistical models describe the sewer condition as a random variable. Models take into account the probabilistic nature of the deterioration processes and use historical data to provide correlations between deterioration factors and condition data.

Cohort survival model

The cohort survival model describes the deterioration process of homogenous sewer pipe groups (i.e. cohorts) sharing similar deterioration factors with transition functions. Each transition function determines the transition from one condition state into the next worse condition state. Transition functions do not integrate deterioration factors as covariables. Therefore, the prediction of the deterioration behavior within a cohort (pipe group) is an average estimation for all pipes belonging to the group. Cohort survival models cannot be used with accuracy to predict the deterioration of each individual pipe but may be useful to support strategic asset management, i.e. the definition of long term strategies and budget requirements.

The cohort model has been investigated in detail by Baur and Herz (2002) in Germany and by Hörold (1998) in Norway. The model has been widely applied in Germany. Several tools using a cohort survival model are proposed mainly by German consulting offices (e.g. AQUA-WertMin, DynaStrat, KANEW-Z). In general, these tools aim to predict rehabilitation needs and costs for different investment scenarios. They can be used to describe the relationship between budget allowance and the resulting development of the sewer network condition. More information about available software can be found in DWA (2012).

Model description

Sewers pass through different conditions during their service life. The sewer condition is evaluated based on CCTV using discrete classification methods (e.g. RERAU, DWA M149-3; for more information on classification methods see Kley *et al*. (2013)). It is assumed that sewers survive with some probability a number of years within a particular condition. The transition from one into the next condition is described by condition survival curves that are also known as transition functions. Transition functions need to be calibrated for each defined sewer group (i.e. "cohort"). Information regarding deterioration factors is used to create homogeneous cohorts.

Several distributions (e.g. Weibull, Gompertz, Herz) are suitable to estimate the transition functions. The Herz distribution was developed to model the deterioration of water supply pipes and is particularly suitable as it models the deterioration process according to the "bath tube curve" (Figure 4): after some time of resistance in the best condition state, the failure probability starts to increase exponentially up to the median age and then turn into a declining curve approaching a finite maximum value (Baur and Herz, 2002). At this last stage, the pipe does not deteriorate anymore by getting older.

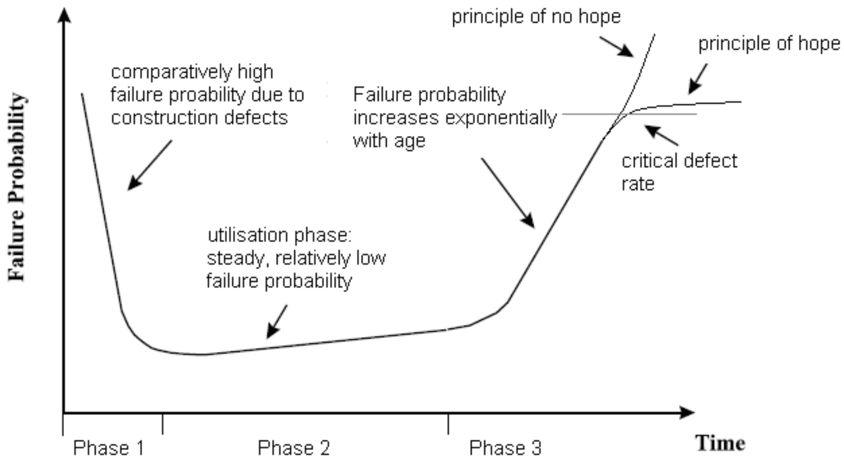

Figure 4: 'Bath tube' curve (from Herz, 1999): graphical description of the deterioration process

The so called "survival" function of the Herz distribution describes the transition from condition *i* to *i*+1 (Herz, 1995, 1996):

$$S(t)_{i\to i+1} = \frac{a_{i\to i+1}+1}{a_{i\to i+1}+e^{b_{i\to i+1}(t-c_{i\to i+1})}} \qquad (1)$$

where

- $S(t)_{i\to i+1}$ is the fraction of pipes at age *t* that have survived until condition *i* or better,
- *a* is the aging factor. The larger *a* is, the smoother is the transition.
- *b* is the transition parameter. The larger *b* is, the faster is the transition

- *c* is the resistance time and determines the age when no further deterioration takes place

Calibration

The parameters *a*, *b*, and *c* of the Herz survival or transition function can be estimated by minimizing R^2 that presents the deviation between the calibrated transition function $S(t)_{i \to i+1}$ and the observed fraction of sewers in condition *i* or better (Baur *et al*., 2004). The calibration of the transition function requires data on sewer installation year, inspection year and condition state for a representative sample of sewers of each cohort.

Prediction

The transition curves can be used to predict the remaining life of pipes (time needed to reach the transition curve toward the worst sewer condition). Figure 5 gives an example of calibrated transition functions from a real dataset and presents the forecasting process (Hörold, 1998). For a group of sewers of about 50 years and found to be in condition class 3 following CCTV inspections, the first pipe of the group to reach condition class 5 (worst condition) will reach it after 48 years (minimal Remaining Service Life RSL of the group). The last pipe of the group to reach condition 5 will reach it after 105 years (maximum RSL of the group). The average RSL of the pipe group is 80 years.

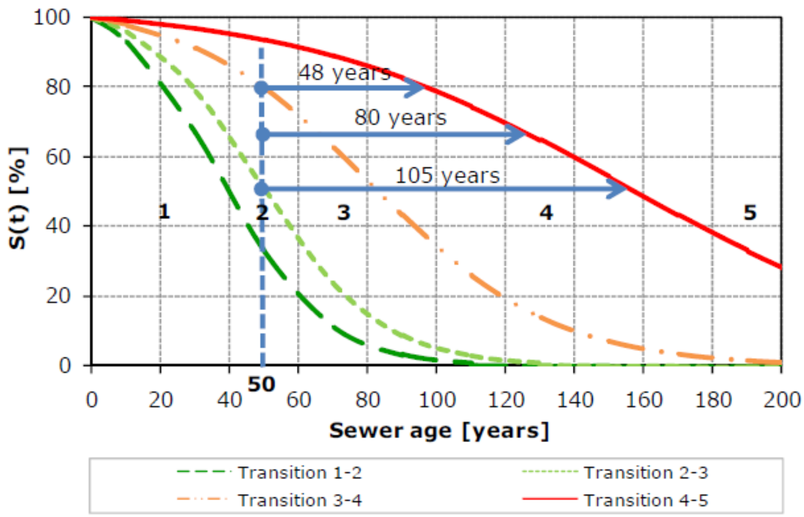

Figure 5: Transition functions for a Norwegian network and prediction of the sewers remaining service life (from Hörold (1998) cited by Ana (2009)).

Advantages: The advantage of the cohort survival models lies in its conceptual and computational simplicity.

Limitations: The cohort survival model requires an extensive dataset to create cohorts with sufficient inspected sewers in each condition state. The model needs enough condition data to create cohorts with similar deterioration characteristics. On the other hand, it needs a sufficient amount of inspection data in each condition state to calibrate the transition functions. Each cohort must be small enough to be considered homogenous, but large enough to provide results that are statistically significant (Kleiner *et al*., 2007).

Most of the times, not enough pipes have been inspected for certain sewer types or condition states (Ana and Bauwens, 2010). The samples of sewers used to calibrate the transition functions are rarely totally random since the operator may focus his inspection strategy on a specific type of sewer (e.g. sewers in very poor condition, old sewers, sewer of a specific area). Le Gat (2008) suggests correcting model calibration against this bias by introducing weights so that the model represents the various conditions in a balanced way.

Additionally, the prediction of the remaining service life of individual pipes is prone to high errors due to the large variations of lifetimes between individual pipes.

Markov model

Markov-chains are a stochastic process that describes the behavior of systems that pass through a finite or countable number of possible condition states. It is a random process characterized as 'memoryless' due to the key assumption that the prediction of a future condition only depends on the current condition and is independent of the sequences of events that preceded it. At each time step, the system may change its condition state from the current to another worse condition or remain in the same condition, according to a given probability.

Markov-chain theory is a widely used methodology for the prediction of the future condition of infrastructures such as road pavements, bridges or drinking water networks (Le Gat, 2008). Several tools using Markov theory have been developed for sewer systems during the last 15 years (e.g. STATUS, Gompitz, KANEW-Z). Le Gat (2008) developed the GompitZ model within the research project Care-S. The GompitZ algorithm has been integrated in the software KANEW-Z proposed by the engineering and software company 3S Consult GmbH (3SC). More information about available software can be found in DWA (2012). Furthermore Ana (2009), Baik *et al*. (2006), Mehle *et al*. (2001), Micevski *et al*. (2002), Tran (2007), and Wirahadikusumah *et al*. (2001) have demonstrated applications of the Markov model to predict sewer pipes structural deterioration.

Model description

The transition probabilities are expressed mathematically as *m* x *m* matrix Q, where *m* is the number of possible condition states and *i* = *m* is defined as the worst condition state. The sum of row elements is always 1 and the pipe cannot improve its condition state without intervention and rehabilitation activities. To simplify the calculation, it can be assumed that each condition state can only transit to the next worse condition state so most parts of the matrix are equal to zero (Le Gat, 2008).

$$\mathbf{Q}\ (t,t+1)=\begin{bmatrix} q_1(t,t+1) & 1-q_1(t,t+1) & 0 & 0 \\ 0 & q_i(t,t+1) & 1-q_i(t,t+1) & 0 \\ 0 & 0 & q_{m-1}(t,t+1) & 1-q_{m-1}(t,t+1) \\ 0 & 0 & 0 & q_m(t,t+1)=1 \end{bmatrix} \quad (2)$$

where

- $q_i(t,t+1)$ is the probability that the pipe stays in condition *i* between time *t* and *t+1*
- $1-q_i(t,t+1)$ is the probability that the pipe transits in the next worse condition between time *t* and *t+1*

The transition probabilities can be time independent (i.e. homogenous Markov model), or time dependent (i.e. non-homogenous Markov model) (Ana and Bauwens, 2010). Non-homogeneous Markov models are usually used to simulate sewer deterioration since transition probabilities depend on the sewer age and older sewers may deteriorate faster (Kleiner, 2001). In the case of semi-Markov models, the transition probabilities do not only depend on the current condition state of the sewer, but also on the time already spent in the current state (Dirksen and Clemens, 2008). It assumes that the time spent in each condition state is randomly distributed (Kleiner, 2001).

Calibration

The transition probabilities are derived from condition survival functions (e.g. Weibull or Gompertz distribution, similar as cohort survival models). Survival functions are calibrated for predefined pipe groups sharing the same features (similar to the cohort model, cohorts are created based on available data regarding deterioration factors) and can additionally consider deterioration factors as covariables (Le Gat, 2008). In this case, data regarding deterioration factors are included in the mathematical definition of the survival functions (see Le Gat (2008)). The parameters of the transition functions are estimated by minimizing the deviation between the calibrated transition function and the observed sewer condition data.

Prediction

Transition probabilities can be used to simulate the expected condition of the sewers in the future. The condition state vector *p(t)* indicates the probability distribution of condition states at any time *t* according to the calibrated survival functions (Figure 6). The probability vector *p(t+1*) at time *t+1* can be obtained by multiplying the current condition state vector $p^T(t)$ by the transition matrix *Q(t,t+1).* More generally, to obtain the probability distribution at time *t+s*:

$$p^T(t+s) = p^T(t)\prod_{i=1}^{s} Q(t,t+i)\,. \tag{3}$$

Figure 6 gives an example of survival functions calibrated using inspection data from the city of Dresden (Germany) and shows the condition state vector at age 100 (Le Gat, 2008).

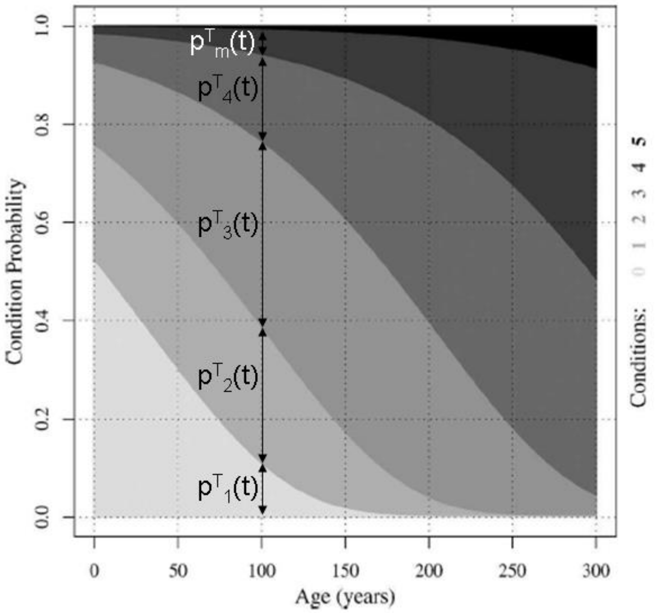

Figure 6: Gompertz condition survival functions related to a stormwater concrete pipe of the Dresden sewer system, Germany, and an example of a state vector at age 100 (from Le Gat (2008))

Advantages: Unlike the cohort survival model, Markov models can consider pipe specific covariates in the calibration of the transition functions. Therefore, the amount of homogenous sewer groups (cohorts) can be reduced, because additional deterioration factors can be integrated as parameters in the survival functions.

In addition, the outcomes of the Markov model are not condition states, but condition probabilities that can be implemented in a risk-based approach (Ana and Bauwens, 2010). For example, Le Gat (2008) developed a Markov-based approach that enables to rank the rehabilitation priorities according to the probability of pipes being in a poor condition.

Limitations: The calculation of the transition probabilities requires a large amount of inspection data representative of each pipe group for different condition states and ages. Especially, data of repeated inspection that reflect the condition changes of individual pipes over time are often missing (Le Gat, 2008).

Logistic regression analysis

Regression methods can be used to determine the probability of failure of individual pipes. The logistic regression is a type of regression analysis used for predicting the outcome of a categorical variable (e.g. discrete sewer condition classes). Generally, the outcome is defined by two categorical dependent variables (binary logistic regression). The logistic regression can also be generalized by allowing more than two discrete outcomes (multinominal logistic regression) (Silva *et al*., 2013).

Several types of regression have been tested for the prediction of sewer condition. Ariaratnam *et al*. (2001) developed a binary logistic regression for the prediction of the likelihood that a sewer is in a deficient state for the sewer network of Edmonton, Canada. Salman (2010) applied logistic regressions on inspection data of the city of Cincinnati (USA). Chughtai and Zayed (2008) applied multiple regression techniques to develop sewer condition models using deterioration factors as predictor variables.

Model description

Logistic regression can be considered as a special type of linear regression in which the dependent variable is transformed into the logit of the probability of failure (Salman, 2010):

$$\log (p / 1- p) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \quad (4)$$

where

- p is the probability for a pipe to be in a good condition state
- $1-p$ is the probability for a pipe to be in a failed condition state
- X_i are the independent variables (e.g. deterioration factors: age, pipe size, depth, etc.)
- α and β_i are the offset and slope of the regression

Possible multi-colinearities among variables X_i need to be checked (e.g. using the Wald Test) in order to exclude irrelevant variables and redundant information. Indeed, if two variables are strongly correlated, there is no need to integrate both in the regression. Therefore, the model considers only factors that have a significant influence on the sewer condition.

In order to calibrate the model, the binary outcome is estimated from condition classes based on CCTV results: e.g. the worst two conditions classes represent the failed condition state and the other condition classes represent sewers in good condition. The parameters α and β can be calculated using the maximum likelihood estimation (Salman, 2010) to maximize the agreement of the output with observed data.

Advantages: The logistic regression model is a simple concept, which provides a direct prediction of the probability of pipes failure that can be used for risk analysis. Furthermore, the regression enables a better understanding of the deterioration process since deterioration factors are directly correlated to the sewer condition (Ana and Bauwens, 2010).

Limitations: The logistic regression model requires a large amount of data about factors affecting the sewer deterioration process in order to obtain good estimates of the regression coefficients (Ana and Bauwens, 2010). According to (Salman, 2010), the linear regression between condition rating and independent variables is not always able to represent the complex deterioration processes.

Multiple discriminant analysis

The aim of discriminant analysis is to estimate the linear relationship between a single categorical dependent variable (i.e. e.g. discrete sewer condition classes) and a set of quantitative independent variables (e.g. deterioration factors). The method is similar to the logistic regression but differs in the estimation of the coefficients. While the logistic regression makes no assumptions on the distribution of the explanatory data, discriminant analyses have been developed for normally distributed explanatory variables. Therefore, discriminant analysis is expected to give better results if the normality assumptions are fulfilled, but in all other situations logistic regression should be more appropriate (Pohar *et al*., 2004).

A multiple discriminant analysis was applied by Tran *et al*. (2006) to model the deterioration of stormwater pipes and by Ana (2009) to predict the deterioration of individual pipes of two sewer networks (Leuven and Antwerp).

Model description

The discriminant analysis uses a set of linear functions of independent variables (e.g. deterioration factors) to determine classification functions:

$$L_i = \alpha + \beta_{i1}X_1 + \beta_{i2}X_2 + \ldots + \beta_{in}X_n \quad (5)$$

where

- L_i is the classification function where $i = 1$ to $k-1$, with k being the number of condition classes
- X_i are the independent variables (e.g. deterioration factors: age, pipe size, depth, etc.)
- β_{ij} are the classification coefficients that correspondent to n-number of independent variables
- α is the offset

To describe the methodology, each sample of inspection data can be visualized as a point in a n-dimension space. Classification functions L_i are new estimated axes in a $k-1$ dimensional space that enables to separate each point into clusters of condition classes. Each condition class has a central position ("centroid") in this new space that can be calculated by taking the mean values of each factor. For a new prediction, a point is considered to belong to a condition class if its distance to the class centroid is smaller than to the other class centroids. Figure 7 shows a classification example with $k = 3$ condition classes. Therefore it has $k-1 = 2$ axes (L_1 and L_2) that have been created to represent the samples into clusters of condition classes. The new prediction is decided to be in condition class 3 as it is very close to its centroid.

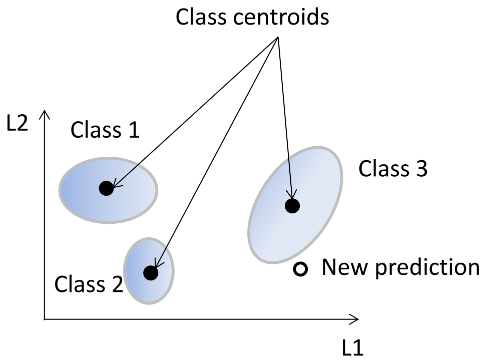

Figure 7: Illustration of a discriminant analysis classification with three condition classes (adapted from Tran (2007)).

The determination of the coefficients β_i can be done by maximizing the variance between classes. Maximizing this ratio is also called Fisher's criterion. Just like in the regression analysis, the significance of each factor and possible correlations between independent variables have to be analyzed in order to exclude irrelevant ones.

Advantages: The discriminant analysis seems to be a robust methodology to handle output of ordinal data and take into account the probabilistic nature of sewer deterioration (Tran, 2007). Besides, similar to a regression analysis, the method aids the better understanding of the deterioration process by relating the most important factors that influence the deterioration process to sewer conditions.

Limitations: The method requires assumptions on the distribution of the predictor variables that could represent drawbacks in its applicability.

2.1.3 Artificial intelligence models

Neural networks NN

Neural networks can be used to predict output data from input data in a manner that simulates the operation of the human nervous system. Similar to the human brain, an network of artificial neurons is created in which each neuron receives input signals and produces output signals. The models structure does not require any assumption and is defined by the sample data (data driven). Generally, the models can handle ordinal outputs such as condition classes and can simulate non-linear relationships within the deterioration process.

In the case of sewer deterioration modeling, neural networks investigate the mathematical relationships between predictors (independent variables, i.e. deterioration factors) and responses (dependent variables, i.e. discrete sewer condition classes) by "learning" the deterioration behavior of pipes from inspection data. The knowledge from the sample data is generalized to predict the condition of new pipes (Tran *et al*., 2007).

Khan *et al*. (2010) designed and evaluated neural networks using the commercially available model software "Neuroshell2" (WardSystemsGroup, 1996). Tran *et al*. (2007) also demonstrated the application of neural networks using sample data of the city of Greater Dandenong (Australia).

Model description

Generally, a neural network is composed of artificial neurons that are connected to each other and ranged in different layers. Each connection between neurons has an associated weight that is determined by minimizing the error between the predicted output and the actual output value using observed data (Salman, 2010). The dataset used to train the network contains (i) sewer deterioration factors, which are used as input values and (ii) condition states of inspected sewer pipes that represent the outputs of the model.

Two main neural networks used for deterioration modeling are the back-propagation neural networks (BPNN) and the probabilistic neural networks (PNN). The main principles of these methodologies are presented below. For more detailed information, refer to Ana (2009), Marlow *et al*. (2009) or Tran (2007).

→ *Back propagation neural networks (BPNN)*

The BPNN is a neural network that simulates the sewer degradation using values X_i of deterioration factors and calibrated connection weights. The model is basically composed of three layers (Figure 8).

- In the input layer, each node represents a deterioration factor with a value $X_{i.}$
- In the hidden layer, each node receives signals from the input layer. The inputs X_i in the previous layer are multiplied by associated connection weights. The connection weights are an analogous to the coefficients of statistical models and need to be adjusted during the training process. The weighted inputs of each node are summed and an output signal is produced using pre-defined mathematical functions (also called transfer or activation functions). The number of neurons of the hidden layer is identified during the training process.
- The neurons of the output layer receive signals from the hidden layer and define the predicted condition classes.

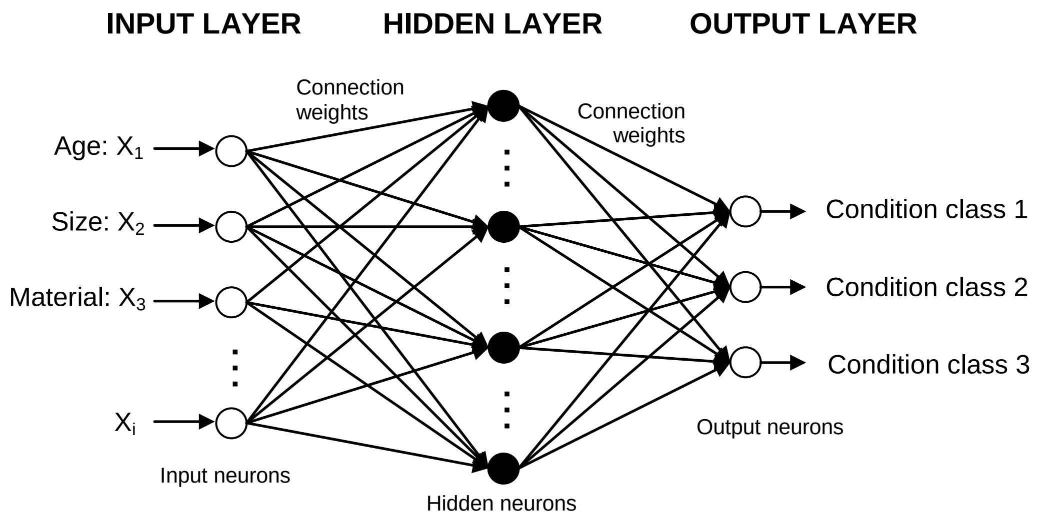

Figure 8: Schematic presentation of the back propagation neural network BPNN (adapted from Tran *et al*. (2007))

The calibration (referred as training process) of the neural network is achieved by repeatedly feeding the model using new examples of input and output data. Optimization algorithms are used to adjust the model coefficients (i.e. the connection weights) in order to minimize the error between predicted and observed condition classes.

→ *Probabilistic neural networks (PNN)*

PNN is a special form of neural network based on Bayesian classification rules. Typically, it uses four layers as shown in Figure 9. Each layer is developed using signals from the previous layer:

- The neurons of the input layer represent the values X_i of the deterioration factors.
- In the pattern layer, each sample used for the training is represented by a node. A value is calculated for each node as the product of his input vector X with a weight vector. The nodes are grouped in clusters, according to their condition class.
- In the summation layer, each condition class is represented by a node. The value of each node is computed from the values of the pattern layer using an estimation of the probability density function (PDF) (for more details see e.g. Ana (2009) or Tran *et al*. (2007)).
- In the output layer, Bayesian classification rules are carried out to assign a condition class. For example, for two condition classes (1 and 2), a sample with a vector of deterioration factors X will be classified in condition 1 if

  $$h_1 \cdot f_1(X) > h_2 \cdot f_2(X) \quad (6)$$

  where

  - h_i is the *a priori* probability that X belongs to condition class i
  - f_i is the probability density function for condition class i

During the training process, an optimization algorithm is used to adjust the parameters of the probability function. The PNN model has a faster calibration process compared to the BPNN, because the number of neurons is fixed by the model structure and should not be determined using an additional optimizing process. However, PNN models are based on statistical techniques that make assumptions on the probability distribution and the model structure.

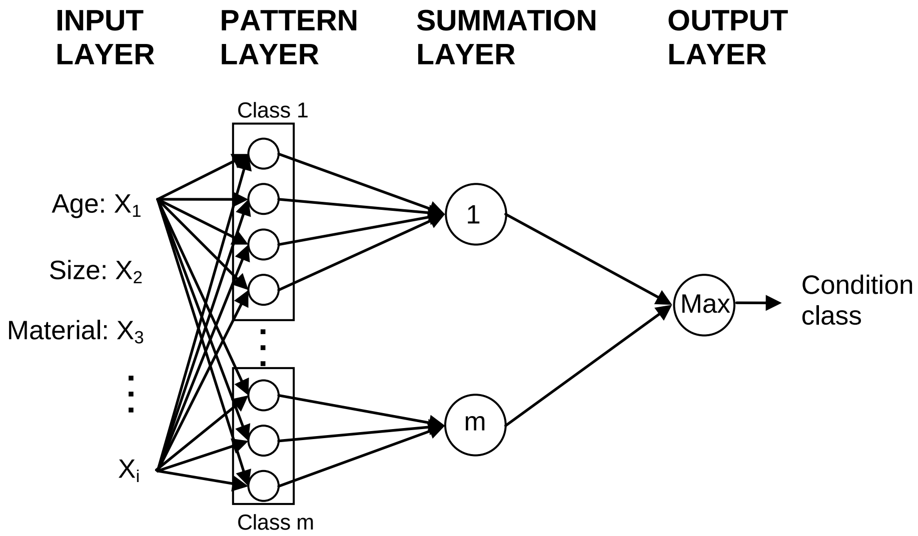

Figure 9: Schematic presentation of the probabilistic neural network PNN (adapted from Ana (2009))

Advantages: Neural Network models can automatically detect and reproduce non-linear and complex underlying processes by analyzing relationships between input and output data. These models can handle scale and ordinal data and are a practical alternative to theoretical models if casual relationships are poorly understood (Tran, 2007).

Limitations: Like all data-driven models, the training of neural network models has a high demand on inspection data. Furthermore, the understanding of the trained NN process is limited since they fall into the category of 'black box' models with hidden underlying processes (Tran, 2007).

Fuzzy set theory

Fuzzy set theory can be used to predict sewer deterioration using engineering judgment and operator experience (Marlow *et al*., 2009). These models are particularly suited when the data are scarce and the information available is expressed in qualitative (linguistic) terms, e.g. "poor", "medium" and "good" condition (Kleiner *et al*., 2006).

Figure 10: Fuzzy set representation of the condition of a 50 years old pipe (from Kleiner *et al*. (2006) cited by Marlow *et al*. (2009))

Fuzzy models convert qualitative (linguistic) description of deterioration factors (e.g. age, defects, condition classes) into fuzzy numbers. Fuzzy numbers refer to a set of possible values for a pipe factor. For example, pipe age can be expressed in linguistic terms as new, young, medium, old or very old. A given pipe age can be transformed into a fuzzy number as a vector A = (μ_1, μ_2, …, μ_n) representing the membership to each age period. Figure 10 shows an example of a fuzzy set A = (0, 0, 0.52, 0.4, 0) from a pipe at age 50. Therefore, the pipe is arranged between the age periods medium and old.

A set of rules (i.e. weights) can then be used to aggregate fuzzy inputs to one fuzzy output. These rules generally include knowledge of the mechanisms of sewer failure and consequences of failure and are based on expert opinion.

Rajani *et al*. (2006) presented how the condition of an inspected pipe can be classified as a fuzzy set. This fuzzy condition classification is done in three steps:

- Fuzzification of coded defects: coded pipe defects (termed 'distress indicators, e.g. cracks, joint displacements etc.) are translated into fuzzy sets. For each distress indicator seven linguistic constants are assigned (excellent, good, adequate, fair, poor, bad, failed) according to its specific quantification.
- Aggregation of distress indicators to categories: a category reflects a specific pipe component (e.g. external coating, inner lining, joint). Distress indicators are combined to reflect the level of deterioration of each category. The combination is based on weighting and the importance of each distress factor according to expert opinion. The results are fuzzy sets for each category.
- Aggregation of categories towards condition rating: expert opinion is used to assign relative weightings to categories in order to calculate the fuzzy condition rating of the pipe. The result is a 7-element fuzzy set, which represents the membership values describing the condition rating from excellent to failed. For example a resulting fuzzy set C = (0,0,0,0.40,0.60,0,0) presents a pipe being to 40 % in a fair condition and to 60 % in a poor condition state.

Expert Systems

The Water Environment Research Foundation (WERF) developed the Expert System SCRAPS (Sewer Cataloging, Retrieval, and Prioritization System) that assesses the probability and consequence of failure of sewer pipes. The methodology can be used to prioritize sewer inspections, especially by small utilities where their available data is scarce (Merrill *et al*., 2004). The method is based on the understanding of all variables that may lead to sewer failure and facilitates the effective use of available data to support inspection strategies.

The system intents to reproduce the decision-making process of an expert by using information stored in a knowledge database. The database has been developed from a literature review and from interviews with experts from partner cities. It consists in a set of rules that characterize possible pipeline failure situations. The system relates the available data concerning sewer characteristics and deterioration factors with the rules defined in the knowledge database to compute the probability that a sewer pipeline may be subject to failure using Bayesian probability theory. The consequence of failure is also estimated using reconstruction costs, land use data and vulnerability data. Finally, the expert system ranks the calculated pipe failure and consequence probabilities of the pipes in order to assign the need and frequency of inspections.

The validation of the tool has been performed making comparisons between model results and expert evaluation for 12 example pipes in a specific condition. Results indicated that the model assessed 75% of the case studies similarly to the utility expert.

2.1.4 Summary of models advantages and limitations

	Cohort	Markov	Logistic regression	Discriminant analysis	Neural Networks
Model level					
Pipe group level	X	X	X	X	X
Pipe level		(X)	X	X	X
Advantage					
Conceptual and computational simplicity	+		(+)		
Understanding of deterioration process: direct relation between factors and condition states			+	+	
Calculation of condition probabilities: appropriate for risk-based approach		+	+		
Appropriate for non-linear and complex processes					+
Limitation					
Need for extensive dataset: deterioration factors + CCTV	-	-	-	-	-
Assumptions on the distribution of the predictor variables				-	
Binary outcome			-		
“Black box” model: hidden underlying processes					-
Complex and time-consuming training processes					-

2.2 Model validation

The validation of deterioration models is a key step to build the confidence of end-users (utilities, municipalities) regarding the models use. Indeed, deterioration models can be successfully used only if decision makers trust the modeling results and are aware of the model uncertainties.

The validation process aims to demonstrate if the model has a satisfactory range of accuracy consistent with his intended application (Schlesinger *et al*., 1979 cited by Sargent, 1999). The accuracy of deterioration models can be evaluated by comparing model predictions with “real” data, i.e. observed values. Generally, the comparison is done using data that were not used during the calibration procedure. This may be done by splitting the available dataset in two sets dedicated respectively to calibration and validation (about 60-70 % and 40-30 % respectively). The validation is based on historical data so the validation results define the quality of prediction of the model within the time period of the data used for the validation. However, if inspection data are available over the entire lifespan of the sewers, it can be assumed that the future behavior of the network will be estimated with the same prediction quality. This assumption can lead to a bias, especially for the prediction of the evolution of younger parts of the networks, where inspection data is not available over the entire life span of the sewers.

Only very few case studies intended to evaluate the quality of prediction of models (e.g. Ana, 2009; Chughtai and Zayed, 2008; Ens, 2012; Khan *et al*., 2010; Le Gat, 2008; Salman, 2010; Tran, 2007). Results are hardly comparable since (i) the data available for model calibration differ (percentage of CCTV available, type of deterioration factors available) and (ii) the metrics of the methodologies used to assess the quality of prediction differ.

The next chapters present firstly the validation methodologies used for the validation of deterioration models. Secondly, validation results from several applications of deterioration models on full-scale case studies are discussed.

2.2.1 Validation methodologies

Several methods have been proposed in the literature to assess the quality of prediction of models.

- At the pipe group level, the goodness-of-fit is mostly used to evaluate whether the observed number of pipes differs from the predicted number of pipes for each condition.
- At the pipe level, indicators derived from the confusion matrix are mostly used to summarize the number of correctly and incorrectly predicted observations. The quality of the prediction of regression based models is often assessed using the coefficient of determination or the Root Mean Square Error.

If several methods have already been proposed in the literature, there is still a lack of consensus regarding the most adapted methodologies to really demonstrate the ability of models to simulate sewer condition.

Confusion matrix

When comparing model prediction with observed values, three possible situations can be observed:

- True prediction (TP): when the model correctly predicts the sewer condition (e.g. poor or good sewer condition)
- False negative (FN): when the model incorrectly predicts the sewer condition as a positive case (e.g. sewer in poor condition predicted as being in good condition)

- False positive (FP): when the model incorrectly predicts the sewer condition as a negative case (e.g. sewer in good condition predicted as being in bad condition)

False negative predictions are particularly critical since they lead to an overestimation of the sewer condition: costs associated to failed or collapsed sewers are much higher than inspection costs to verify the condition state of a false positive sewer (Tran, 2007).

The confusion matrix summarizes the number of correctly and incorrectly predicted observations. The confusion matrix enables to assess the three possible situations described above. Table 2 shows an example of confusion matrix with three condition classes by comparing the predicted condition states with observed condition states. The same matrix can be done for n condition classes, depending on the number of grades.

Table 2: Example of confusion matrix for model validation with three condition classes

		Observed condition			**Total**
		1 (good)	**2 (fair)**	**3 (poor)**	
Predicted condition	**1 (good)**	TP_{11}	FN_{12}	FN_{13}	P_1
	2 (fair)	FP_{21}	TP_{22}	FN_{23}	P_2
	3 (poor)	FP_{31}	FP_{32}	TP_{33}	P_3
Total		O_1	O_2	O_3	

The total model efficiency E_{tot} can be calculated as the ratio of correct predicted values on total observed values:

$$E_{tot} = \frac{TP_{11} + TP_{22} + TP_{33}}{O_1 + O_2 + O_3} \tag{7}$$

The efficiency E_j of the prediction of each condition class j can be calculated as:

$$E_j = \frac{TP_{ij}}{O_j} \tag{8}$$

The false Negative rate *FNR* can be calculated for each condition class j as:

$$FNR_j = \frac{\sum_i FN_{ij}}{O_j} \tag{9}$$

The indicators of the confusion matrix are useful to evaluate the quality of prediction of pipe level models, since prediction results are available for each sewer. However, the confusion matrix cannot be used at the pipe group level.

Goodness-of-fit

The goodness-of-fit test is a statistical test used to determine whether the observed number of pipes differs from the predicted number of pipes for each condition. The Pearson chi-squared test (χ^2) is a well-known goodness-of-fit test based on a null hypothesis that the observed frequency is matched with the estimated (or predicted) frequency (Tran, 2007). The chi-square is calculated using:

$$\chi^2 = \sum_i \left(\frac{(nO_i - nP_i)^2}{nP_i} \right) \tag{10}$$

where nO_i is the observed number of pipes in condition i, and nP_i is the predicted number of pipes in condition i.

The chi-square value can be used to calculate the p-value considering the number of degree of freedom. The null hypothesis is rejected if χ^2 is higher than the critical $\chi^2_{0.05,2}$ (95% confidence level and 3-1=2 degree of freedom). It means that the predicted number of pipes differs significantly from the observed number of pipes.

Coefficient of determination

The coefficient of determination R^2 is a widely used statistical parameter that indicates the degree up to which a model is able to capture the variability of the observed data (Khan *et al*., 2010).

Root Mean Square Error

The Root Mean Square Error can be used to measure the difference between predicted and observed values.

$$RMSE = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(O_i - P_i)} \qquad (11)$$

with O_i = observed value, P_i = predicted value, and n = number of observed value.

Average Invalidity and Validity Percents

The average invalidity and validity percents (*AIP* and *AVP*) are used by Chughtai and Zayed (2008) and Khan *et al*. (2010) to evaluate the quality of prediction. An *AIP* value close to "0" means there is a negligible element of error in the model performance. An *AVP* value close to "0" implies that the model does not simulate the observed values accurately.

$$AIP = \frac{1}{n}\sum_{i=1}^{n}\left|1 - \frac{P_i}{O_i}\right| \qquad (12)$$

$$AVP = 1 - AIP \qquad (13)$$

2.2.2 Validation results in international case studies

Case studies in Belgium

Ana (2009) applied several deterioration models (cohort survival, semi-Markov, logistic regression, Multiple Discriminant Analysis MDA and Probabilistic Neural Network PNN) on sewer and inspection data of the city of Leuven and Antwerp, Belgium. For the city of Leuven, the models were applied using 1255 samples equivalent to 50 km of sewers (total sewer length is 400km): 1000 samples were used for calibration and 255 for validation. For the city of Antwerp, 1539 samples were available with all data, i.e. 63 km of sewers. The structural condition of CCTV samples has been evaluated using the Dutch classification methodology (NEN3399, 1992). The following deterioration factors were considered for model calibration: sewer age, material, function, shape, size, depth, length, slope, and traffic intensity (high, medium, low).

The models used are divided into pipe group (cohort survival, semi-Markov) and pipe-level models (logistic regression, Multiple Discriminant Analysis MDA and Probabilistic Neuronal Network PNN). Pipe group models are evaluated using the chi-square goodness-of-fit whereas pipe level models are evaluated using an indicator from the confusion matrix: the total model efficiency E_{tot}. Pipe group models cannot be evaluated using the confusion matrix since results are not available for each sewer but for groups of sewers. Results are shown in Table 3 for the Leuven network but are similar for the Antwerp network.

For the pipe group models, the quality of prediction has been evaluated using the chi-square statistic χ^2. The cohort survival model seems appropriate to predict the sewer deterioration with a 95% significance level. On the other hand, the χ^2 value for the semi-Markov model shows insufficient prediction quality due to an overestimation of the deterioration. The cohort survival model seems to be the most reliable pipe group model for this case study.

For the pipe-level models, the efficiency has been calculated from the confusion matrices. The logistic regression and the PNN show good overall prediction quality. However, it has been shown that they fail to predict sewers in condition 1 and 2 (poor condition) accurately and are rather able to predict the condition of sewers in good condition states (for details see Ana (2009)). It is assumed that the models show a low prediction power for sewers in bad conditions because only few data of sewer in bad conditions were available. Furthermore, these models may produce absurd predictions such as sewer improving in condition, as they get older.

Table 3: Evaluations of the prediction quality of the models tested in Leuven (adapted from Ana (2009))

Deterioration models	**chi-square values χ^2 (< $\chi^2_{0.05,2}$ = 5.99)**	
	Calibration dataset	**Validation dataset**
Cohort model	1.4	1.3
Markov model	330	82

Deterioration models	**Total model efficiency E_{tot} (%)**	
	Calibration dataset	**Validation dataset**
Logistic regression	90	90
MDA	60	60
PNN	95	80

Case studies in Australia

Tran (2007) applied several deterioration models in the City of Greater Dandenong in Victoria (Australia). A dataset of 417 concrete pipes was available among the entire population of stormwater pipes (3.4% of the total length). The dataset was randomly spitted in a calibration (75%) and a validation (25%) dataset. The structural condition of CCTV samples has been evaluated using the Sewer Inspection Reporting Code of Australia (WSAA, 2002). The following deterioration factors were considered for model calibration: sewer age, shape, size, depth, slope, soil type, pipe location (e.g. under road or under nature strip), tree count, and hydraulic condition (good, fair or poor).

The performance of several models has been tested and compared to identify the most reliable model between Markov model, Multiple discriminant analysis (MDA), Ordered probit (type of ordinal regression, not described here), Back Propagation Neural network (BPNN) and Probabilistic neural network (PNN).

The Markov model is used to predict the structural deterioration at the pipe-group level and can be evaluated using the Pearson chi-square statistic. The remaining four models can be used at the pipe group and pipe level and are evaluated using the chi-square and the total model efficiency E_{tot} from the confusion matrix.

For the pipe group models, results indicate that the Markov model, the BPNN and PNN passed the goodness-of-fit test (Table 4) and thus are suitable to predict sewer deterioration. The Markov model has the lowest chi-square value and hence shows the best performance in predicting sewer deterioration in this case study.

Table 4: Chi-square values for the application of five deterioration models in the City of Greater Dandenong (adapted from Tran (2007))

Deterioration models	**chi-square values χ^2 (< $\chi^2_{0.05,2}$ = 5.99)**	
	Calibration dataset	**Validation dataset**
Markov model	0.22	0.34
MDA	12.9	14.5
Ordinal regression	7.21	7.35
BPNN	2.13	2.57
PNN	1.97	4.21

For the pipe-level models, the BPNN was found to be the best model according to the total model efficiency E_{tot} for the calibration dataset (Figure 11). The BPNN ranked second but performed better for the validation dataset, the ordinal regression ranked third and the MDA ranked fourth.

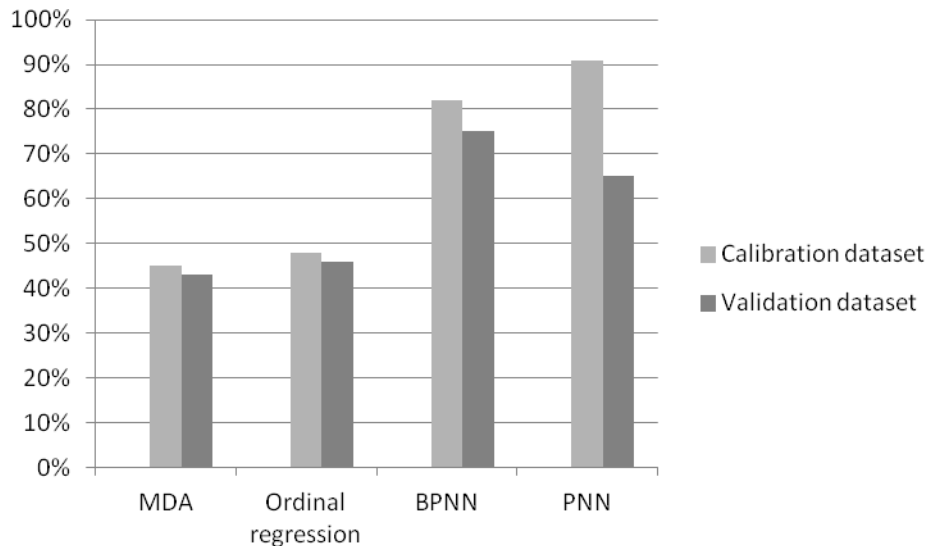

Figure 11: Total model efficiency E_{tot} for the application of the pipe level models in the City of Greater Dandenong (adapted from Tran (2007))

Case studies in Canada and U.S.A.

Ens (2012) applied a logistic regression model on the data of a Canadian municipality. 1315 records were available but only 200 were used to provide an unbiased dataset between poor and good sewer conditions. The structural condition of CCTV samples has been evaluated using the WRc procedures (WRc, 2004). The model was calibrated considering age, condition and material. Results indicate that the model does not fit well with the data. According to Ens (2012) the logistic regression model may not be appropriate for the dataset or the use of other deterioration factors should be considered.

Salman (2010) applied several deterioration models on inspection data of the city of Cincinnati (USA). The finalized dataset was composed of 11373 records: 80% were selected randomly for the calibration dataset and respectively 20% for the validation dataset. The structural condition of CCTV samples has been evaluated using the PACP procedures (NASSCO, 2007). The following deterioration factors were considered for model calibration: sewer age, material, function, size, depth, length, slope, and road class. The selected deterioration models focused on the pipe level: ordinal regression (not presented here), multinomial logistic regression and binary logistic regression analysis.

For the ordinal regression, necessary model assumptions were not met so the model cannot be used for sewer deterioration. As an alternative, the multinomial logistic regression was tested with three condition classes (poor, fair and good). The total model efficiency E_{tot} was 53% but prediction efficiency for condition class 2 is about 10%. This means the model failed to predict more than 90% of sewers in condition class 2 (Table 5).

Table 5: Validation results from the application of the multinomial regression in the city of Cincinnati (USA) (adapted from Salman (2010))

		Observed condition		
		1 (good)	**2 (fair)**	**3 (poor)**
Predicted condition	**1 (good)**	521	245	166
	2 (fair)	48	59	61
	3 (poor)	238	315	622
Efficiency E_i		65 %	10 %	73 %

The binary logistic regression analysis has been applied after deriving two condition classes from the initial condition scores: poor and bad condition. The total model efficiency E_{tot} was 66% (Table 6). Prediction efficiency for good condition is 78% and for bad condition 46%.

Table 6: Validation results from the application of the binary logistic regression in the city of Cincinnati (USA) (adapted from Salman (2010))

		Observed condition	
		0	**1**
Predicted condition	**0 (good)**	1112	460
	1 (poor)	314	389
Efficiency E_i		78 %	46 %

Chughtai *et al*. (2008) used a multiple regression model to simulate the condition state of sewers using data from two Canadian municipalities (Pierrefonds and Niagara Falls). The structural condition of CCTV samples has been evaluated using the WRc procedures (WRc, 2004). The following deterioration factors were considered for model calibration: sewer age, material, function, size, depth, length, slope, bedding factor, and street category.

The coefficient of determination (R^2) indicates that the developed regression models can explain 72 to 88% of the total variability in the structural and operational sewer conditions. The AVP (average validity percent) is found to be within the range 82 to 86%.

Khan *et al*. (2010) also developed deterioration models using data from Pierrefonds. They used neural network modeling with back propagation (BPNN) and probabilistic (PNN) approaches. 20% of the available data were divided to test the model. The coefficient of determination (R^2) ranged within 71 and 86% depending on the deterioration factors considered.

Case studies in Germany

Le Gat (2008) developed a statistical deterioration model based on non-homogeneous Markov chains (NHMC). The model is implemented in the GompitZ software and was applied using inspection data of the city of Dresden (Germany). A subset of 7042 (287 km) concrete pipes was used to calibrate (75% of the subset) and validate (25%) the model. The structural condition of CCTV samples has been evaluated using the DWA procedures (DWA, 1999) The pipe diameter, installation period, and the type of effluent have been considered as covariates for the creation of the transition functions.

The model has been validated using a methodology based on the ability of the models to identify sewers in poor condition. The method is presented below.

For each of the 1748 pipes selected for the validation, the vector of predicted condition probability is multiplied by a condition score vector to obtain a degradation score $x_i(t_i)$ that represents the predicted condition of each pipe

$$x_i(t_i) = p_i(t_i)^T \cdot k \qquad (14)$$

with

- $p_i(t_i) = (p_{0i}(t_i), p_{1i}(t_i), p_{2i}(t_i), p_{3i}(t_i), p_{4i}(t_i), p_{5i}(t_i))^T$, is the vector of predicted probability, i.e. the prediction of the condition states probabilities of each inspected sewer at the age of the inspection (6 condition states, 5 being the worse condition),
- $k = (0, 1, 2, 3, 4, 5)^T$, is the condition score vector

The degradation score $x_i(t_i)$ will be particularly high if a pipe is predicted in very poor condition. Le Gat (2008) proposes to sort the predicted pipes in decreasing order according to their degradation score and then to represent the cumulative rank of the predicted pipe in function of the cumulative number of pipes in condition 5, the worst condition (Figure 12).

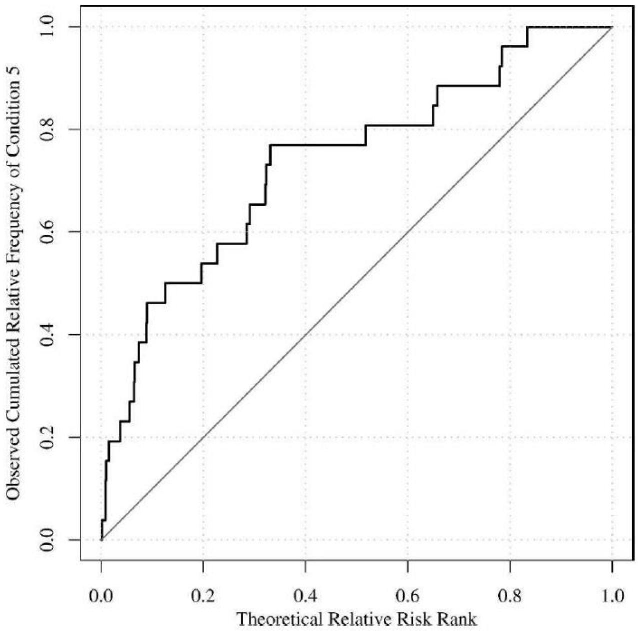

Figure 12: Cumulative rank of predicted pipes (y) in function of cumulative number of pipes in condition 5 (from Le Gat (2008))

The farther the curve departs from above the first diagonal, the more efficient the model is to detect the most deteriorated pipes (Le Gat, 2008). The curve begins with a very high slope and is above the bisector. It means that a large amount of pipes predicted in poor condition are actually in poor condition. According to Figure 12, 50% of the pipes in condition 5 have the 20% worst predicted degradation scores. This kind of approach underlines the interest to use such tools to identify sewer in poorest condition.

2.2.3 Summary of validation results

Since the validation methodologies and the data available for model calibration and validation differ, there is no clear conclusion about the best modeling approach at the pipe and pipe group levels. Furthermore, some models have been tested in several case studies (e.g. Markov models) whereas other models have been evaluated only once (e.g. Cohort model). Table 7 summarizes the main results from the case studies.

Ana (2009) found out that the cohort survival model is the most useful model at the pipe group level. However, even considering the simplicity of the approach, no other validation results have been found in the literature. Main reason could be the need of very extensive dataset to create sewer groups (cohorts) with sufficient inspected sewers in each condition state. Further research is needed to confirm the findings of Ana (2009) and demonstrate the benefits of the approach for strategic planning.

Numerous projects (Ana, 2009; Baik *et al*., 2006; Mehle *et al*., 2001; Micevski *et al*., 2002; Tran, 2007; Wirahadikusumah *et al*., 2001) have presented the application of Markov based models to predict sewer pipes structural deterioration. However only very few of them provided validation results to conclude about their reliability. Ana (2009) found out that the Markov based models show insufficient prediction quality due to an overestimation of the deterioration. On the other hand, Tran (2007) concluded that the Markov model is suitable for sewer deterioration modeling and Le Gat (2008) demonstrated the benefits of using a Markov based approach for finding the sewers in the poorest condition. The quality of prediction of Markov models depends on the reliable calibration of the transition probabilities and thus on the availability of a large amount of inspection data. Especially, data of repeated inspection that reflect the condition changes of individual pipes over time are often missing (Le Gat, 2008). New applications of Markov model using extensive inspection dataset are required to conclude about their ability to simulate the deterioration process at both pipe group and pipe levels.

Logistic regression and Multiple Discriminant Analysis (MDA) have been tested on several dataset but showed pretty low prediction performances (Ana, 2009; Ens, 2012; Salman, 2010; Tran, 2007). The low prediction ability of MDA could be explained by non-valid statistical assumptions on the normality of the input factors (Ana, 2009). The low performance of logistic regression could originate (i) from a biased distribution of the datasets in terms of number of samples for each condition state or (ii) from the lack of data for important deterioration factors (Ana, 2009). However, Chughtai and Zayed (2008) managed to build regression models using deterioration factors to predict sewer condition grades with pretty encouraging validation results. These findings underline the potential of regression methods to provide a better understanding of the deterioration process at the pipe level if sufficient data regarding deterioration factors are available.

Neural networks have proven to be successful tools for the prediction of the deterioration of individual pipes (Khan *et al*., 2010; Tran, 2007). However, results were not satisfying in the case study of Ana (2009). Main reason could be the lack of data to train the model: CCTV were available for less than 15% of the network.

Table 7: Validation results from the application of different sewer deterioration models in the literature: C for cohort survival models, M for Markov models, R for regression based models (including Discriminant Analysis) and N for neural networks. (+) indicates that the validation results are rather satisfying, (-) indicates that the model failed (or partially failed).

Study	**City**	**Samples used**	**Model tested**				**Results**
			C	**M**	**R**	**N**	
Ana (2009)	Antwerp Belgium	1539	+	-	-	-	• C is appropriate at the pipe group level • M fails at the pipe group level • R and N fail at the pipe level
Tran (2007)	Greather Dandenong Australia	417		+	-	+	• M is appropriate at the pipe group level • N is the best at the pipe level
Ens (2012)	Canadian city	200			-		• Very low prediction quality
Salman (2010)	Cincinnati USA	11373			-		• R has overall good prediction quality but fails to predict sewer in medium condition
Chughtai and Zayed (2008)	Pierrefonds and Niagara Falls Canada	-			+		• Good prediction quality
Khan *et al*. (2010)		-				+	• Good prediction quality
Le Gat (2008)	Dresden Germany	7042		+			• Good prediction quality

Conclusion and perspectives

This report has first described the potential sewer deterioration factors and analyzed a panel of literature case studies regarding the relevance of each factor on sewer deterioration. Results are hardly directly comparable, because of the different construction practices, historical backgrounds and environmental conditions of the networks investigated. However, some trends regarding the most significant factors may be identified. In most studies, the construction year and the material seem to be the most relevant factor to explain sewer aging. Pipe size, depth, location and sewer function show generally a medium significance on sewer deterioration. Pipe slope was found to have a low significance for the structural deterioration but a high relevance on the hydraulic deterioration.

In its second part, this report has introduced three main approaches for sewer deterioration modeling: deterministic, statistical, and artificial intelligence based models. Previous researches found out that deterministic models are too simplistic to reflect the entire deterioration process. They usually rely on a number of simplifying assumptions and do not account for the uncertainty that is associated with asset deterioration and failure (Marlow *et al*., 2009). Promising approaches are statistical and artificial intelligence models that use historical data to relate deterioration factors to sewer condition.

Only very few case studies intended to evaluate the quality of prediction of these deterioration models. Furthermore, validation results are often contradictory and hardly comparable since (i) the data available for the calibration differ (percentage of CCTV available, type of deterioration factors available) and (ii) the metrics of the methodologies used to assess the quality of prediction differ. Furthermore, some models have been tested in several case studies (e.g. Markov models) whereas other models have been evaluated only once (e.g. cohort survival model). There is still **no clear conclusion about the best modeling approach** depending on the modeling purpose (pipe group or pipe level).

There is also **no clear conclusion regarding the quality of prediction that can be reached**. The validation results presented in the case studies depend strongly on the quality and quantity of the input data available to calibrate the models, i.e. sewer condition classes and data regarding the potential deterioration factors. In most case studies, only a small percentage of CCTV data was available and much data regarding potential deterioration factors was missing.

Indeed, due to the cost of CCTV inspection, only few utilities have already performed a full inspection of their entire sewer systems. If too little data is available, the subset used for model calibration is probably not representative for the entire network and will lead to poor modeling results.

Data concerning the factors that influence sewer deterioration are not systematically gathered by sewer operators. If main data about age, material and size are mostly available, other data that may have a significant influence on sewer deterioration are rarely available. For example, the factors pipe location (surface loading), soil type, sewer bedding and presence of trees (influence of roots) have been rarely investigated since few data are available in the operator databases. As far as known to the authors, the influence of other potential significant factors, such as installation method, standard of workmanship, joint type and ground water level has not been investigated quantitatively. Since these factors are often considered to have a major influence on sewer deterioration, further studies are needed to gather data and analyze their influence of sewer deterioration along with the classical sewer characteristics.

Even if data regarding deterioration factors are available in the operator databases, they are rarely exhaustive. For example, the information about sewer material or sewer construction year could be available only for a part of the network. Incomplete data can be used to calibrate deterioration models but the influence of partial information on the quality of modeling results should be carefully evaluated.

Thus, it is hard to conclude whether the low prediction performances in the presented case studies depend more on the poor dataset available than on the model ability itself. The potential of deterioration models is still to be evaluated on case studies using comprehensive datasets of both CCTV and deterioration factors. More generally, the influence of the amount of CCTV and data regarding deterioration factors available on the prediction quality of deterioration models should be carefully investigated. This step is crucial to inform sewer operators about the optimum data requirement for the successful use of deterioration models.

Bibliography

Allouche E N, Freure P, 2002, *Management and Maintenance Practices of Storm and Sanitary Sewers In Canadian Municipalities*, ICLR Research, Paper Series No. 18, http://www.iclr.org/images/Management_and_maintenance_practices.pdf.

Ahmadi M, Cherqui F, De Massiac J-C, Le Gauffre P, 2013, "Influence of available data on sewer inspection program efficiency", *Urban Water Journal*, Article in Press.

Ana E V and Bauwens W, 2007, *Sewer network asset management decision-support tools: a review*. Int. Symp. New Directions in Urban Water Management, UNESCO, 12-14 September 2007, Paris, France.

Ana E V, 2009, *Sewer asset management - sewer structural deterioration modeling and multicriteria decision making in sewer rehabilitation projects prioritization,* PhD thesis, Department of Hydrology and Hydraulic Engineering, Vrije Universiteit Brussel, Brussel.

Ana E V, Bauwens W, 2010, "Modeling the structural deterioration of urban drainage pipes: The state-of-the-art in statistical methods", *Urban Water Journal* **7** 47-59.

Ana E V, Bauwens W, Pessemier M, Thoeye C, Smolders S, Boonen I, De Gueldre G, 2008, *Investigating the effects of specific sewer attributes on sewer ageing - a Belgian case study*, 11th International Conference on Urban Drainage, Edinburgh, Scotland, UK.

Ariaratnam S T, El-Assaly A, Yang Y, 2001, "Assessment of infrastructure inspection needs using logistic models", *Journal of Infrastructure Systems* **7** 160-165.

ASCE, 2009, *Report card for America's infrastructure*, American Society of Civil Engineers, Available from http://www.infrastructurereportcard.org/index.

Baik H S, Jeong H S, Abraham D M, 2006, "Estimating transition probabilities in Markov chain-based deterioration models for management of wastewater systems", *Journal of Water Resources Planning and Management* **132** 15-24.

Baur R, Herz R, 2002, "Selective inspection planning with ageing forecast for sewer types", *Water Science and Technology* **46** (6-7) 389-96.

Baur R, Zielichowski-Haber W, Kropp I, 2004, *Statistical analysis of inspection data for the asset management of sewer networks*, Proceedings 19th EJSW on Process Data and Integrated Urban Water Modeling, Lyon, France.

BS EN 1295-1, 1998, *Structural design of buried pipelines under various conditions of loading - Part 1: General requirements*, British Standards Institution, Publication Date: June 15th, 1998.

Chughtai F, Zayed T, 2008, "Infrastructure condition prediction models for sustainable sewer pipelines", *Journal of Performance of Constructed Facilities* **22** 333-341.

Davies J P, Clarke B A, Whiter J T, Cunningham R J, 2001, "Factors influencing the structural deterioration and collapse of rigid sewer pipes", *Urban Water* **3** 73-89.

Dirksen J, Clemens F H L R, 2008, "Probabilistic modeling of sewer deterioration using inspection data", *Water Science and Technology* **57** (10) 1635-41.

DWA, 1999, *ATV-M 143-2: Inspektion, Instandsetzung, Sanierung und Erneuerung von Abwasserkanälen und -leitungen –Teil 2: Optische Inspektion*, Deutsche Vereinigung für Wasserwirtschaft, Abwasser und Abfall, April 1999.

DWA, 2012, *Synopse - Leitfaden zur strategischen Sanierungsplanung von Entwässerungssystemen außerhalb von Gebäuden*, DWA-Themen, Deutsche Vereinigung für Wasserwirtschaft, Abwasser und Abfall e. V.

Ens A, 2012, *Development of a Flexible Framework for Deterioration Modeling in Infrastructure Asset Management,* Master of applied science, Department of Civil Engineering, University of Toronto, Toronto, Canada.

Herz R, 1995, " Alterung und Erneuerung von Infrastruturbeständen - ein Kohoertenüberlebensmodell", *Jahrbuch für Regionalwissenschaft Jg. 14/15,* p. 5-29*.*

Herz R, 1996, "Aging Processes and Rehabilitation needs of Drinking Water distribution networks", *Journal of Water Resources Planning and Management* **45** 221-231.

Herz R, 1999, *Bath-tubes and hammock-chairs in servie life modelling*, Proceedings of the 13th Junior Scientist Workshop in Rathen, pp. 11-17, Lehrstuhl Stadbauwesen, TU Dresden.

Hörold S, 1998, *Forecasting Rehabilitation Needs: Evaluation of the Aqua WertMin software for service life and total cost estimation*, SINTEF *Report* (SINTEF Technology and Society, Trondheim, Norway).

Kawabata T, Uchida K, Ariyoshi M, Nakase H, Mohri Y & Ling H, 2003, *D.E.M. Analysis on Behavior of Shallowly Buried Pipe Subject to Traffic Loads*, Pipelines 2003, ASCE, pp.139-148.

Khan Z, Zayed T, Moselhi O, 2010, "Structural condition assessment of sewer pipelines", *Journal of Performance of Constructed Facilities* **24** 170-179.

Kleiner Y, 2001, "Scheduling inspection and renewal of large infrastructure assets", *Journal of Infrastructure Systems* **7(4)** 136-143.

Kleiner Y, Sadiq R, Rajani B B, 2006, "Modeling the Deterioration of Buried Infrastructure as a Fuzzy Markov Process", *Journal of Water Supply Research and Technology, Aqua* **55** 67-80.

Kleiner Y, Rajani B, and Wang S, 2007, *Consideration of static and dynamic effects to plan water main renewal*, Proceedings Middle East Water 2007, 4th International Exhibition and Conference for Water Technology, Manama, Bahrain.

Kley G, Kropp I, Schmidt T, Caradot N, 2013, *Review of available technologies and methodologies for sewer condition evaluation*, KWB report, project SEMA, 2013, p 41, Berlin, Germany.

König A, 2005, *WP2 External Corrosion Model Description*, Computer Aided REhabilitation of Sewer networks (Care-S)*,* SINTEF Technology and Society, Trondheim, Norway.

Le Gat Y, 2008, "Modeling the deterioration process of drainage pipelines", *Urban Water Journal* **5** 97-106.

Marlow D, Davis P, Trans D, Beale D, Burn S, 2009, *Remaining Asset Life: A State of the Art Review*, Final Report, Water Environment Research Fundation (WERF), Alexandria, VA, US.

Mehle J, O´Keefe, Wrase P, 2001, *An Examination of Methods for Condition Rating of Sewer Pipelines*, Center for development of technical leadership, University of Minnesota.

Merrill M S, Lukas A, Palmer R N, Hahn M A, 2004, *Development of a tool to prioritize sewer inspections*, Water Environmental Research Foundation (WERF), Virginia, USA.

Micevski T, Kuszera G, Coombes P, 2002, "Markov model for storm water pipe deterioration" *Journal of Infrastructure Systems* **8(2)** 49-56.

Modica G R, 2007, "The History of the newark Sewer System", in *The New Jersey Homepage of the American Local History Network* (http://www.usgennet.org/usa/nj/state/EssexNewarkSewer.htm).

Müller K, Dohmann M, 2002, *Entwicklung eines allgemein anwendbaren Verfahrens zur selektiven Erstinspektion von Abwasserkanälen und Anschlussleitungen*, Bundesministerium für Bildung und Forschung (bmb+f), Aachen, Germany.

Müller K, 2006, *Strategien zur Zustandserfassung von Kanalisationen,* Dissertation, Aachener Schriften zur Stadtentwässerung, Institut für Siedlungswasserwirtschaft der RWTH Aachen, 2006.

NASSCO (National Association of Sewer Service Companies), 2007, *Pipeline Assessment And Certificate Program (PACP)*.

NEN3399, 1992, *Sewerage systems outside buildings – Classification for visual inspection of sewers*, Nederlands Normalisatie Instituut.

O'Reilly M P, Prosbrook R B, Cox G C, McCloskey A, 1989, "Analysis of defects in 180 km of pipe sewers in southern water authority", *TRRL Research Report 172.*

Pohar M, Blas M, and Turk S, 2004, "Comparison of Logistic Regression and Linear Discriminant Analysis: A Simulation Study", *Metodološki zvezki* **1(1)** 143-161.

Rajani B, Kleiner Y, and Sadiq R, 2006, "Translation of Pipe Inspection Results Into Condition Ratings Using The Fuzzy Synthetic Evaluation Technique", *Journal of Water Supply Research and Technology-Aqua*, **55**, 11-24.

Salman B, 2010, *Infrastructure Management and Deterioration Risk Assessment of Wastewater Collection Systems*, PhD thesis, University of Cincinnati.

Sargent RG, 1999, *Validation and Verification of Simulation Models*, Proceedings of the 1999 Winter Simulation, eds., P.A. Farrington, H.B. Nembhard, D.T. Sturrock, and G.W. Evans, pp. 39-48.

Schlesinger *et al.*, 1979, "Terminology for model credibility", *Simulation* 32, 3, p103-104.

Scheidegger A, Hug T, Rieckermann J, Maurer M, 2011, "Network condition simulator for benchmarking sewer deterioration models", *Water Research* **45** 4983-4994.

Schmidt T, 2009, *Modellierung von Kanalalterungsprozessen auf der Basis von Zustandsdaten,* PhD thesis, Institut für Stadtbauwesen und Straßenbau, Technical University Dresden, Dresden, Germany.

Silva A, Gaspar P., de Brito J., 2013, “Probabilistic Analysis of the Degradation Evolution of Stone Wall Cladding Directily adhered to the substrate”, *Journal of Materials in Civil Engineering*, **25(2)**, 227-235.

Tran D, 2007, *Investigation of deterioration models for stormwater pipe systems,* PhD thesis, School of Architectural, Civil and Mechanical Engineering, Victoria University.

Tran D, Perera A W M, Davis P, 2006, "Application of probabilistic neural networks in modeling structural deterioration of stormwater pipes", *Urban Water Journal* **3 (3)** 175-184.

Tran D H, Perera B J C, Ng A W M, 2007, *Neural network based prediction models for structural deterioration of urban drainage pipes*, Land, Water and Environmental Management: Integrated Systems for Sustainability, Proceedings, Christchurch pp 2264-2270.

Tuccillo M E, Jolley J, Martel K, Boyd G, 2010, *Report on condition Assessment of Wastewater Collection Systems*, EPA, United States Environmental Protection Agency, Cincinnati, Ohio.

Vollersten J, König A, 2005, *WP2 Report D6: Model testing and evaluation*, Computer Aided REhabilitation of Sewer networks (Care-S)*,* SINTEF Technology and Society, Trondheim, Norway.

WardSystemsGroup, 1996, *Neural network products for the next generation: Neroshell2 theoretical manual*, Ed F Ward systems Group Inc, Md.

Wirahadikusumah R, Abraham D, Iseley T, 2001, "Challenging issues in modeling deterioration of combined sewers", *Journal of Infrastructure Systems* **7** 77-84.

WRc, 1986, *Sewerage Rehabilitation Manual*, Water Research Center, London, U.K.

WRc, 2004, *Manual of Sewer Condition Classification - 4th Edition*, Water Research Centre, UK.

WSAA, 2002, *Sewer Inspection Reporting Code of Australia*, Water Service Association of Australia (WSAA), Melbourne.