Future inspection and deterioration prediction capabilities for buried distributed water infrastructure

Makana, Lewis; Shepherd, W.; Tait, S.; Rogers, Chris; Metje, Nicole; Boxall, J.B.; Schellart, A.N.A

DOI:
10.1061/(ASCE)PS.1949-1204.0000656

Title: Future Inspection and Deterioration Prediction Capabilities for Buried Distributed Water Infrastructure.

Authors: Makana L.O.[1], Shepherd W.[2], Tait S.[3], Rogers C.D.F.[4], Metje N. [5], Boxall J.B.[6], Schellart A.N.A.[7]

1. **Corresponding Author**
   Position/Title: Research Fellow
   Professional Designations: MEng, PhD, GMICE
   Affiliation: Department of Civil Engineering, University of Birmingham, UK
   Mailing Address: Department of Civil Engineering, University of Birmingham, Edgbaston, B15 2TT, UK
   Email: l.makana@bham.ac.uk
2. **Position/Title**: Research Associate
   Professional Designations: MEng, PhD
   Affiliation: Department of Civil and Structural Engineering, University of Sheffield, UK
   Mailing Address: Sir Frederick Mappin Building, Mappin Street, Sheffield, S1 3JD
   Email: w.shepherd@sheffield.ac.uk
3. **Position/Title**: Professor of Water Engineering
   Professional Designations: BSc, PhD
   Affiliation: Department of Civil and Structural Engineering, University of Sheffield, UK
   Mailing Address: Sir Frederick Mappin Building, Mappin Street, Sheffield, S1 3JD
   Email: s.tait@sheffield.ac.uk
4. **Position/Title**: Professor of Geotechnical Engineering
   Professional Designations: BSc, PhD, CEng, MICE, Eur Ing, FCIHT, SFHEA
   Affiliation: Department of Civil Engineering, University of Birmingham, UK
   Mailing Address: Department of Civil Engineering, University of Birmingham, Edgbaston, B15 2TT, UK
   Email: c.d.f.rogers@bham.ac.uk
5. **Position/Title**: Professor of Infrastructure Monitoring
   Professional Designations: Dipl.-Ing., PhD, MCInstCES, MASCE, FHEA
   Affiliation: Department of Civil Engineering, University of Birmingham, UK
   Mailing Address: Department of Civil Engineering, University of Birmingham, Edgbaston, B15 2TT, UK
   Email: N.Metje@bham.ac.uk
6. **Position/Title**: Professor of Water Infrastructure Engineering
   Professional Designations: MEng, PhD, CEng, CEnv, FCIWEM
   Affiliation: Department of Civil and Structural Engineering, University of Sheffield, UK
   Mailing Address: Sir Frederick Mappin Building, Mappin Street, Sheffield, S1 3JD
   Email: j.b.boxall@sheffield.ac.uk
7. **Position/Title**: Senior Lecturer in Water Engineering
   Professional Designations: MSc, PhD
   Affiliation: Department of Civil and Structural Engineering, University of Sheffield, UK
   Mailing Address: Sir Frederick Mappin Building, Mappin Street, Sheffield, S1 3JD
   Email: a.schellart@sheffield.ac.uk

Abstract: This paper examines the role for pipe deterioration prediction approaches for optimising maintenance, repair and rehabilitation of buried water supply, wastewater collection and drainage networks. It is appreciated that there are other ancillary assets within water supply and wastewater collection and drainage networks, but these were not considered in this paper. Currently there are a range of asset condition assessment frameworks, mainly based on asset defect location, identification and characterisation. These are

infrequently applied in practice, mainly due to the restricted availability of asset defect inspection data. The paper reviews current deterioration modelling approaches and highlights the crucial need for broader, richer data sets (including both asset and surrounding environment data) to inform the development and application of such approaches. The paper describes what could be considered as an expanded "ideal" data set for deterioration modelling at a network and individual asset scale and indicates emerging new inspection technologies that should be capable of meeting the enhanced data needs.

Keywords: Deterioration Modelling, defect classification, inspection capabilities, data needs, water supply and wastewater collection networks.

1.0 Introduction

One of the fundamental needs of human settlements is a source of clean water – without this, people cannot survive. To this basic need should be added the facility to remove wastewater and also deal with excessive surface water arising from precipitation and overland and ground flows. Water supply pipes normally operate under pressurized conditions, in which the internal pressure varies but is always higher than atmospheric pressure, wastewater collection and storm water drainage systems generally operate in an unpressurized state. In developed countries, the systems have been in operation for a very long time, have been constructed from a wide variety of materials, and have been progressively added to. The materials that make up these buried pipe networks are naturally subjected to chemical, physical and biological stresses, and the pipe networks typically therefore suffer from deterioration over time in a variety of ways. Those operating these networks are responsible for maintaining adequate quality of service delivery, and therefore an understanding of when the systems are likely to fail, or deteriorate to a point of adversely influencing the service provision, is vital. Failure of both water supply, wastewater collection and drainage networks can be defined as an inability to carry the required flows, whether that be wastewater flows, stormwater rainfall runoff flows, or supplying potable water demand and maintaining the ability to pass even higher flows for firefighting purposes. Pipes should also convey flows with acceptable levels of exfiltration/infiltration and leakage and for water supply water networks quality should also be above specified thresholds.

From this simple introduction, it can be argued that these water infrastructures are the lifeblood of cities across the world, and failure to function adequately and deliver their services can lead to considerable social, economic and environmental losses (Ana and Bauwens 2010). Potable water pipe infrastructures are often stated to have a service life of 50-120 years (Ormsby 2009; Li et al. 2014), although many pipelines currently in operation in the UK and other countries greatly exceed this upper limit, hence failures can be expected. Makar et al. (2020) contend that the cost of such failures could amount to £thousands to £millions in repair and replacement costs, and collateral damage to the overlying (roads in towns and cities) and adjacent buried infrastructures. To these direct costs, that can range up to 80% of what utilities spend (Hukka and Katko 2015), should be added the multiple forms of social and environmental costs caused by disruption to urban systems and damage to the natural environment. This simply serves to emphasise the need to understand pipe condition and how it impacts on system performance, intervening using an array of asset management practices before failures occur.

The chief concern in infrastructure asset management is the maintenance of service of an adequate quality without (undue or lengthy) disruption to service in an effective and cost efficient manner. In many countries water supply, wastewater collection and drainage networks are required to deliver defined levels of service, for example in the UK these networks should not exceed a particular number of service supply interruptions or number of flooding incidents (National Archives 2008). Network operators consequently try to link the ability of their infrastructure to meet these defined levels of service (system performance) with the physical characteristics of individual assets (condition); this in turn enables assessment of asset condition to inform robust decision-making on where and when to repair, rehabilitate or replace vulnerable assets. Deterioration models inevitably have a role to play in this decision-making, and yet all this relies upon comprehensive and accurate condition assessment.

The goal of buried pipeline condition assessment is commonly too narrowly-focussed: buried pipelines only perform structurally if adequately supported by the ground, and hence it is the complete pipe-soil system that needs to be assessed and understood. Extending this argument further, it is an appreciation of the complete context in which a pipeline exists that should be sought, leading to the model advocated by Rogers et al. (2017)

of three interdependent infrastructures in the street: the buried infrastructure (water and sewer networks), the surface infrastructure (road structures) and the geotechnical infrastructure (the ground). Treating the ground as an infrastructure enables helpful performance insights, such as the application of deterioration models to the ground. Conversely, without an understanding of the competence of ground support it is impossible to fully appreciate the consequences of defect identification and mapping.

At present sewers and drainage pipelines, and occasionally water supply pipelines, are inspected internally using, for example, cameras or sensors mounted on a tethered platform or sensor platforms inserted into the network, that advect with the flow and are then retrieved after a certain period of time to identify individual defects and so as determine asset condition. Asset condition is then often ranked based on the number and/or severity of individual defects. Crucially, this process does not include an assessment of whether the asset is likely to meet its required service levels and nor does it assess the surrounding context other than by implication in some cases (e.g. a displaced joint might indicate exfiltration and a loss of ground support). Moreover, condition assessment of buried water infrastructure is usually carried out with limited resources and with a piecemeal characterisation and inventory of related systems' features (Oliveira et al., 2007), often resulting in only a small part of any network being regularly and effectively inspected (Tscheikner-Gratl et al. 2019). This results in a far from comprehensive assessment of the asset base, but more like a series of spot checks on lengths of the pipeline network for which there is a cause for concern or an appreciation that failure would have significant consequences.

Deterioration processes relate to both structural and functional deterioration. Structural deterioration processes operate at different rates depending on many contextual features and the various kinds of stresses that occur (Rajani and Kleiner 2001), and thus a spot check in time, even if allied to a deterioration model, provides no assurance of condition understanding significantly into the future. Functional deterioration - the failure to meet functional requirements such as intermittent blockages in sewers or drainage pipes causing flooding or compromised water quality in damaged water pipes (for example contaminant ingress, Fox et al. 2015) - can occur on an even shorter timescale.

A comprehensive assessment of the condition of a pipeline and its context (specifically the competence of the support it received from the ground), allied to an understanding of the mechanisms that cause a pipeline's condition to deteriorate over time and the accompanying impact on performance, are essential in informing and implementing efficient asset management strategies. In relation to this set of requirements, this paper first examines current condition assessment approaches and explores how well current approaches enable robust asset management protocols to be developed. Examining the underlying causes of asset deterioration in buried pipe networks, the paper proposes more appropriate methods for condition assessment and required future inspection needs. Finally, the focus of the paper is extended to considerations of systems-based engineering approaches (Wasson 2015), exploring the interdependencies and interactions with other urban infrastructures, and the synergies that can be leveraged from them, to make condition assessment and deterioration smarter. Although water supply, drainage and sewerage networks comprise of many ancillary elements in addition to the pipes, the focus of this paper is solely on the pipes which form the majority of the spatial coverage of any network. We do not intend to discuss methods of defect identification, but aim for a more comprehensive understanding of what defects future technologies should be capable of assessing to provide better knowledge of pipe condition assessment and deterioration.

2.0 Condition Assessment

Once installed, the pipe structure and the inner wall surface of buried pipes can deteriorate (Kleiner and Rajani 2001). Structural deterioration results in buried pipes having a diminished capacity to resist physical stresses, while deterioration of the inner surfaces of pipes results in a reduction of hydraulic capacity, degradation of water quality, and the diminished capacity to resist internal corrosion. Both categories of deterioration can lead to serviceability failures in pipe systems; the risk of such failure is estimated based on the condition of individual pipes.

At present standardised condition assessment protocols exist and are in regular use in industrial piping, oil and gas pipelines, and wastewater collection systems. A wide ranging field of research studies has been undertaken from the mid-1960s to identify pipeline failure mechanisms and characteristic defects leading to ‘fitness-for-purpose’ and ‘fitness-for-service’ procedures (Younis et al. 2015), the majority of which still underlie many of today’s standard asset condition measurement practices in water and sewerage companies. For example, the UK’s Water Research Centre (WRc) published the first edition of the Manual of Sewer Condition Classification (MoSCC) in 1980 and this framework is currently in its fifth edition (WRc 2013). There are also similar documents and standards for pipe inspection and classification of defects, and estimation of condition in sewers across the world, including for example EN 13508-2 (2011) in Europe, and IKT (2014) in Germany. The Sewerage Rehabilitation Manual, now re-named Sewerage Risk Management (WRc 2021), was first published in 1983 building on MoSCC to develop an objective based methodology for rehabilitating sewerage networks principally based on observed defects and inferred asset condition. This approach has been refined as system performance requirements changed over time and a more risk based approach became appropriate.

Conversely, no regular standardised condition classification system is in operation to date for water supply pipelines. A plethora of reasons have factored into this situation, comprising but not limited to inadequate funding for water utilities, high inspection costs, the density and complexity of water distribution systems, risk of water contamination, being located underground with limited (if any) access points, pipes made of assorted materials, which by consequence led to use of a wide range inspection technologies and condition assessment schemes (Rajani and Kleiner 2001; Li et al. 2014). To-date, limited work has been conducted on synthesising the assessment of different types of defects and by consequence the resulting pipe condition in water distribution pipes, although attempts have been made to develop a framework for an accepted standardised defect classification system for water distribution pipelines (Younis et al. 2015), where recent funded WRF work has attempted to develop a standardised condition classification for water supply systems, but currently more development is needed. The main reason for no standard condition classification system is the enhanced difficulty in collecting defect data in comparison to sewer systems. It is difficult to insert inspection systems in a pressurised environment, there is the risk of contamination which means inspection data is much more limited.

Table 1 lists several of the current protocols used to classify sewer pipe condition into various categories and states, depending on the degree of complexity and context to account for. The different condition classes should not be taken as an objective measure associated with functionality, as they are usually based on defects identified on CCTV images with no causal link to measurable physical characteristics. CCTV inspection practices persist to-date as the most requested method for condition and operational evaluation of sewer systems. Despite the quality of CCTV footage obtained having markedly increased over the past decade, the CCTV approach for sewer inspection continues to be criticised due to subjectively identifying individual defects which do not map directly on asset performance (Dirksen et al. 2013; Van Riel et al. 2014; van Riel et al. 2016; Li et al. 2019).

Currently, there is no single generalised framework to estimate pipe condition that can be used in both water supply and wastewater collection and drainage systems, accounting for an “ideal” data set for deterioration modelling at a network and to indicate emerging new inspection technologies that should be capable of meeting the enhanced data needs. Although historically the management of water supply and sewerage/ drainage networks are generally considered separately, the authors believe that both types of pipe networks have sufficient physical similarities, i.e. systems of buried jointed pipes so that condition assessment protocols could be developed and applicable to both types of network. In both systems there are pressurized pipes that are buried and subjected to time varying loading so that such pipes undergo similar mechanical processes, it is accepted that corrosion processes are different but the mechanical consequences are similar. Clearly, sewer and drainage systems are generally gravity driven, but their loading patterns could be seen as a subset of pressurized pipes“. There are more mature frameworks used in wastewater collection and drainage networks, based on the identification of infrequent defects mainly by the use of CCTV. In water supply networks, frameworks are emerging but their adoption is more challenging as there is no single dominant inspection technology in use in water supply networks, and due to the more restricted access and risks to water quality of invasive methods. In both applications the condition classification schemes do not have a direct and clear link to system performance and serviceability. The inspection technologies used are generally high cost and disruptive so only spatially sparse and infrequently collected data is available meaning that data on the temporal change in the condition of any asset is rare.

3.0 Deterioration Modelling

Buried water supply and wastewater collection network infrastructure asset management usually involves the process of collection of defect data using a range of methods and then mapping the defect data onto corresponding asset condition and occasionally linking this to an assessment of the current performance of pipe networks. It is unusual to directly link asset condition assessments and predictions of service levels from performance models. To be able to estimate future performance of buried pipe networks it is important to be able to estimate the rate of deterioration of individual assets, how these change with time and ultimately impact on system performance.

Deterioration models for predicting the condition and performance of buried water assets are classified as deterministic, statistical, probabilistic, data-driven (artificial neural networks (ANN), Fuzzy Logic (FL)) and heuristic (Boxall et al. 2007; Clair and Sinha 2012). A summary of the different deterioration modelling approaches and their predictive focus and relative data needs can be found in Table 2.

Statistical models that use current and historical maintenance and failure records, are the most common approach used to forecast the number and rate of pipe/asset failures (e.g. Kleiner and Rajani 2001; Boxall et al. 2007; Lawless 2011; Osman and Bainbridge 2011; Scheidegger et al. 2015). Typically, only a handful of data parameters are applied to establish failure rate relationships often based simply on the pipe parameters (Hahn and Shapiro 1994). Pipe networks that have a suitably sizable and dependable historical database are good candidates for statistical models; nevertheless, the usefulness of statistical models is constrained when taking into account newer pipes or other instances with limited historical and/or time dependent data e.g. local environment information such as traffic loading or repair/refurbishment interventions.

Physical probabilistic models involve the application of statistical analysis, particularly in cases where historical failure or inspection data is incomplete or unobtainable (Creighton 2012). The effect that disparate parameters have on pipe performance are what these models specifically analyse as opposed to appraising existing pipe failure records (Rajani and Kleiner 2001). These models claim to have the ability to predict the probability of failure for a network of assets based on an appraisal of individual assets. Typically, they are used where the progression of pipe deterioration and the loading conditions contributing to failure are well characterised.

Data-driven approaches such as Artificial Neural Networks (ANN) have been used to establish pipe deterioration rates by using data on component factors that are assumed to have an effect on the serviceability of the pipe. The advantages of using ANN approaches are their ability to readily deal with nonlinearity as well as inconsistent, messy data, and they can be adaptive to changing circumstances through learning or retraining capabilities for varying data sets (Haykin 2010). The reliability of pipe deterioration rate predictions can be improved by careful selection and data filtering of each of the component input parameters. Machine learning algorithms and corresponding weights can be used to prioritise inspection of these parameters. A barrier to successful implementation of this approach is often the need for an increased level of skill to develop data pre-processing and interpretation methods (Landau 2012). These methods can be employed to develop a model for asset groups for a whole network or an individual asset but are very dependent on the availability of the initial training set (e.g. Wang et al. 2009), hence cohort models dominate due to the sparsity of pipe specific data to learn from.

The use of engineering judgment and professional experience are intrinsically integrated within Fuzzy Logic models that have been used to predict the pipe deterioration process. Where data is scarce or unobtainable, tacit knowledge by way of wide ranging professional experience, then observations and model criteria necessitate expression in ambiguous or “fuzzy” terms is the context where this type of model is used (Sivanandam et al. 2007). This approach does however require significantly less asset data and condition data, than other Machine Learning or statistical approaches to be implemented.

Deterministic models often use failure data from laboratory tests and sample specimens to obtain information required to quantify the associations between component factors that contribute to failures. The relevance of a deterministic model is thus limited to a discrete environment and should not be employed across different environmental settings (Giustolisi et al. 2009). Deterministic models are founded on constrained parameters. Empirical and mechanistic-based or physical models comprise the different types of deterministic models available to estimate pipe deterioration rates. Empirical models are only applicable to assets that are similar, while physical models are often applied to individual assets. Deterministic models that are empirical should only be used on types of pipes that have suitable and dependable historical pipe failure data (Marlow et al. 2009).

Finally, heuristic models are rare as evidenced in Table 2, but can demonstrate how different approaches integrate engineering judgement in the establishment of failure rates (Jones et al. 2002). A constraint of employing engineering knowledge for model development is the wide variation in personal expert judgement and/or limited staff experience in making the required judgments. Nevertheless, the capabilities inherent in this modelling approach offer an improvement in the developed deterioration models by taking into account afterwards more expert knowledge and viewpoints (Alvisi and Franchini 2014).

The contrast of modelling approaches and performances shown in Table 2 is attributable to the number and type of modelling approaches, the size and different types of networks, the diverse gradation of data availability and the assortment of metrics utilised to evaluate the modelling performance. Model performance can be categorised in a twofold manner, contingent on the modelling objective (Ana and Bauwens 2010):

- Network level: the focus here is to simulate the changes in distribution of condition across all assets, often for a particular asset type, in the network over a specified time horizon to inform long-term strategic planning. The metrics reveal to what degree the model can estimate the asset condition distribution of the whole network, i.e. the number of pipes in each condition class against a defined physical characteristic e.g. age or size.
- Pipe level: the focus here is to pinpoint pipes with faults that are in a condition in which failure leading to a severe loss of service is anticipated so as to inform inspection and tactical replacement strategies. The metrics confirm to what degree the model can accurately estimate the inspected condition class of each individual pipe.

A small number of studies have assessed the performance of deterioration models to simulate the condition distribution of the network (Duchesne et al. 2013; Ugarelli et al. 2013; Caradot et al. 2017; Caradot et al. 2018; Hernández et al. 2018). They showed that survival analysis as well as Markov models do better than a simple random model for estimating the evolution of the condition distribution of the network, particularly in the context of limited data availability. Caradot et al. (2018) additionally demonstrated that statistical models have a clear advantage compared to machine learning models at the network level when inferring outside the observation window of the underlying data. Table 2 also highlights the inspection data needs of the different approaches. It is seen that statistically based and ANN based approaches require significant amounts of asset data both in terms of spatial coverage and temporal resolution, as their outputs focus on a single aspect of asset performance and asset type. Probabilistic and heuristic models require less data and the incorporation of tacit data in FL based models require the least amount of training/calibration data in order to deliver consistent predictions of asset deterioration. In an earlier study, Clair and Sinha (2012) highlighted that several water utilities have developed their own deterioration predictive models based on locally available condition data. However, these models generally lack rigour and reliability when compared to models identified in published literature (Table 2). By contrast, many of the models identified in the literature are problematic for water utilities to employ as a result of their demanding data needs.

4.0 Mechanisms for Deterioration

This section examines the physical mechanisms that have been shown to influence the deterioration of buried water supply, sewerage and drainage assets as well as how this knowledge has been used to develop models to estimate the rates of asset deterioration.

There are a wide range of factors that can result in the sudden or progressive damage of pipes. The degree to which each factor has an impact is dependent upon the location where the pipe is installed, the corresponding characteristics of that location, the physical characteristics of the pipe, the operational conditions under which the pipe is exposed to, and installation practice/workmanship which are a big factor in PVC fails for pipes installed in the 1970s and has most recently given fusion joints a bad reputation. The level of influence brought about by each factor should be a consideration when developing a predictive deterioration model (Liu and Kleiner 2013). The factors have been categorised as Dynamic, Static, and Operational which include environmental and physical parameters for water supply systems (Kleiner and Rajani 2002). Additional factors for wastewater collection and drainage systems have been added to Figure 1.

Dynamic factors change over time and are often related to the environment surrounding a pipe. Ismail and El-Shamy (2009) stated that the dynamic factors that contribute to pipe deterioration rates comprise, but are not limited to, corrosivity of soil, flow rate, operating pressure, age of pipe and cumulative number of pipeline breaks. Static factors in contrast remain unchanged over time as regarding properties of the pipe and installation practice, and comprise pipe diameter, pipe material, and type of surrounding soil (El Chanati et al. 2016). Other factors such as bedding material and joint type and design (detailed in Table 3) should also be considered as joints are a major point/mechanism for pipe deterioration and are a very significant area where more data is needed beyond the dearth that now exists in industry.

Operational factors include wastewater characteristics and associated chemical and bioprocesses, sediment level and repair and maintenance policies (Ana and Bauwens, 2010). Operational factors that contribute towards pipe deterioration in water supply networks are water quality, water velocity and hydraulic pressure variations caused by demand patterns and pump operations. The influence of applied pressure on the failure rate of buried water networks was investigated by Shirzad et al. (2014) and also discussed by Rajeev et al. (2014). Stress in the pipe material is the result of water pressure forces (Kabir et al. 2015), which are a derivative of hydraulic demand, inherent structural integrity which is linked to water quality related corrosion (within the pipe material) and the pressures from the surrounding soil which all influence the failure rate in buried water pipes.

Environmental factors that contribute towards deterioration in pipes include ground movements caused by seismic activity, groundwater dynamics and infiltration, freezing and thawing of the soil in which pipes are installed and other nearby engineering activities leading to stress relaxations in the ground (Ismail and El-Shamy 2009). The presence of trees, infiltration and exfiltration, the type of backfill or surface soil and surface loads come under this classification (Ana and Bauwens 2010). Likewise, traffic loads and its accompanying volume needs to be considered as it is directly proportional to the external loading on pipes and their joints, which in some instances are believed to cause cyclic fatigue failures leading to bursts particularly in small diameter pipes (Aydogdu and Firat 2015). The interaction of cyclic loadings (hydraulic transients, daily pressures, traffic and soil movement) have been shown theoretically to dramatically reduce asset lifetime

(Brevis et al. 2016). In addition to the described factors, water quality (alkalinity, electoral conductivity, pH, sulphate attack, residual chlorine, pH, and water temperature) causes pipe corrosion and subsequent deterioration in a water network (Jun et al. 2020). Hydrogen sulphide generation in wastewater can also cause significant deterioration in sewer pipes (Nielsen et al. 2008).

Pipe material is an important factor as different materials have different mechanical properties and so deteriorate or fail in different ways. Pipe material also factors heavily when considering the performance of pipes, more precisely their corrosion resistance and load carrying capacity (Berardi et al., 2008). Historically, the most widely deployed materials for buried water supply and wastewater collection networks are made of concrete, cement, cast iron, polyvinyl and ductile iron. Thick walled pipes exhibit more strength and greater resistance to breakage than thin walled pipes. Thin walled pipes are also more prone to failure as the wall thickness reduces due to corrosion caused by chemical and biological processes, further highlighting the importance of the physical characteristics of the original pipe. Aydogdu and Firat (2015) postulate that the diameter, age and length of the pipe are important factors with respect to deterioration and failure of buried water supply networks. Furthermore, the deterioration rate becomes more pronounced in older pipes chiefly because of legacy challenges that include being exposed to external stresses for long periods of time. Coating and lining are important factors regarding corrosion as coated and lined pipes are less affected by the negative effects of corrosion that increase the deterioration rate (Kutyłowska and Hotloś 2014). Sub-standard installation practices and manufacturing faults of pipes are contributory factors in the deterioration and failure of all types of buried pipes. Premature damage to a pipeline can be attributed to poor installation practices used and to a lesser extent manufacturing faults. The type of joints the pipe has are also an influencing factor in terms of failure (Folkman 2018).

Table 3 summarises key references relating to operational, environmental and physical factors affecting deterioration. Out of the three component groups, the physical factors have the highest number of references. While this might suggest that these are the most important factors, Malek Mohammadi et al. (2020) noted that studies are also influenced by data availability and cost to collect data. Thus data on physical attributes is likely to be more easily and cheaply available, whereas collecting environmental information can be time consuming and expensive.

5.0 Data Requirements for Understanding Pipe Condition and Deterioration

It has been shown that existing methods to understand the current and likely future condition and performance of buried water supply and sewerage pipes are limited by the complexity of the networks, the multiple processes affecting deterioration and the scarcity of data about buried pipe condition, both spatially and temporally, as well as limited data on the external environmental factors. Currently, commonly applied statistically based deterioration models can on the whole only predict the probability of failure, based on cohort modelling and are used by utilities to understand their future whole system rehabilitation needs. This approach does not allow utility owners to know which specific pipes are closest to failure, rather which pipe groups, based on the available data, are at highest risk of failure. Many authors have detailed the "ideal" data requirements needed to create a more effective asset management strategy (Rokstad and Ugarelli 2016; Carvalho et al. 2018) or the 'ideal' data set (Ahmadi et al. 2014). Taking into account the various factors that influence individual asset deterioration listed in Table 3, "ideal" datasets for water utilities would need to be wide ranging and include system and environment characteristics. These are summarised in Figures 2 and 3. These figures show the range of information on asset characteristics during operational life and their surrounding environmental factors but such elements are often missing from utilities' asset databases for various reasons (Makana et al. 2020). Additional difficulties occur when there are inconsistencies relating to historical information such as design drawings and as built drawings (Furlong et al. 2016). There often is a recency bias when such asset information is attainable, and inconsistently collected data dictated by changes in industry reporting standard operating procedures over time or protocols not being followed by water utilities. Despite stringent data requirements and various acquisition method(s), there remains a latent level of error and bias. Other data matters that are noteworthy include misplaced and questionable data, missing information regarding rehabilitation works and the absence of environmental data (Egger et al. 2013).

Furthermore, operators may fail to increase capacity for data storage, and only store the most recent information as part of their data management strategies. This results in inconsistencies in historical data regarding network development, condition, operation and maintenance. Many existing data sets are based on data collected from management and operational processes as well as the asset characteristics (Figure 2). Collecting extra environmental data (Figure 3) is often linked with managing different data owners and traversing differing data quality standards, and needs to be considered when developing data collection plans. Much data may also still require digitisation and storage in relational databases to be useful.

While the condition of an asset can be described from sufficient observations of the physical pipe, the performance of an asset requires additional information. To describe the current performance of an asset, there is a need to understand the required performance to achieve the level of serviceability required by a regulator (e.g. the number of allowable flooding incidents), but also how the pipe condition is affecting performance. For example, as a pipe wall degrades, its hydraulic roughness is likely to increase and cross-sectional area may also decrease (Boxall et al. 2004), thus decreasing the maximum potential flow rate for a given pressure head difference. However, the impact of such condition changes might not be significant, especially in terms of meeting the required level of serviceability. In fact it is expected that the relationship between pipe condition and performance (and achieving levels of serviceability) is highly non-linear. Figure 4 describes a number of conceptual deterioration models describing physical deterioration and the consequent impact on system performance in relation to a required level of serviceability. Physical asset deterioration can be considered to occur linearly (A) in which the physical integrity of an asset deteriorates consistently with time, or an asset suffers an unexpected but sudden loss in physical condition (B) combined with a consistent deterioration rate.

Under the physical deterioration scenario A+B the performance of the asset initially deteriorates slowly (initial phase) and it is only when the pipe has suffered a particular level of deterioration that the performance rapidly deteriorates (second phase). However the link between asset condition and performance is unknown so rate of performance reduction is very uncertain, especially in the second phase (A, B). It is prior to this rapid deterioration in system performance that it is necessary to intervene. Combined with this concept of asset condition and system performance, is the need to meet acceptable levels of performance. Figure 4 clearly indicates that the ability to estimate the time to when system performance becomes unacceptable (optimum intervention point) is strongly related to the rate at which system performance is lost in phase 2. It is clear that for lower levels of serviceability then there is a higher level of uncertainty in determining the optimum time for intervention. This requires new knowledge to link system performance and physical condition, the ability to identify sudden performance loss (C) is also required. These requirements mean that much more frequent and higher spatial resolution of asset inspection data over long time periods, or more adaptive inspection capabilities (in which inspection frequency is linked with the rate of system performance decline) is needed.

Selective survival bias is also an important issue when considering the future development of deterioration models. Most of the current models are projected to underestimate the actual condition of the network as a result of the infrequent asset condition observations used to inform model calibration, selectively accounting for only the pipes that 'survived' until the date of inspection. This leads to a bias as the calibration of models is built on data regarding pipes that are present at the time of inspection, hence underestimating system state, which leads to overestimating the service life of pipes. Egger et al. (2013) suggested that an integration of the deterioration model with a probabilistic replacement model that characterises the probability that the pipe was not replaced at the time of inspection i.e. that the pipe is still in service, would be able to address the selective survival bias issue. More frequent and data sets with higher spatial resolutions would also address this issue.

Currently, the acquisition of data is a costly and disruptive exercise, which explains why data used to develop deterioration models are limited in breadth, depth and quality (Ana et al. 2010). Condition-based maintenance is hampered by limitations in data quality and quantity (space and time), which also impedes the mainstream use of predictive deterioration models; a gap which in-pipe autonomous inspection robots (Fuentes et al. 2017; Thienen et al. 2018; Caffoor 2019; Mounce et al. 2021; Parrott et al. 2020) might overcome. Such new pervasive inspection technologies may also provide a means to adding missing data/metadata. Statistically based models need the most asset data and new inspection technologies, such as in-pipe robotics present the potential for a step change in the management of water supply and sewerage pipes by reducing inspection costs per unit length and disruption, while employing new sensing technologies to better characterise defects and so define condition. Technology could therefore allow networks to be comprehensively and repeatedly surveyed, as well as collecting a broader range of objective data. The data obtained has the potential to transform deterioration modelling and allow utilities to have a higher degree of certainty as to which sections of pipe should be repaired or replaced to maintain performance, while keeping costs to an affordable level. The potential volumes of data however create significant challenges for storage and analysis to allow such assessments to take place. Such practical considerations regarding the management of sewer asset data management are discussed by Tscheikner-Gratl et al. (2019) in some detail.

Our contention is that what is buried within, and above on the ground is to some degree controlled by the soil properties, in the sense that if the soil properties change, or the ground moves, the adjacent and/or overlying elements of the infrastructure respond accordingly (i.e. deform transiently under transient applied loading or deform permanently). To create a buried water pipe infrastructure inspection system able to manage, coherently, what we do to the buried infrastructure (add new elements to it, repair or renovate it, maintain it, or leave it alone – whatever ensures that it delivers the required level of serviceability into the future) we need to be informed by the ground conditions and how the ground might react to that new activity or intervention. The same argument holds for transport infrastructure – e.g. roads, railway, canals, whether on the surface, in cuttings, on embankments or in tunnels. There remain few examples of studies (e.g. Clarke et al. 2017) into the water utility–ground–surface transport infrastructure interdependency as a complete system in terms of their condition, hence their likely future performance and as such what the corresponding data model and data requirements will be in the context of in-pipe inspection robots. This systems approach sets the basis for the ability to go beyond water industry specific data and mix different data sets that will form the new horizon of what data architecture systems are needed to correspond with the deployment of in-pipe inspection robots. A good example in practice of this type of approach to development of data models that attempt to encapsulate multiple data sets for buried water pipe infrastructure, is both the Dutch Gegevenswoordenboek Stedelijk Water data model (RIONED 2017) and Swiss data model (VSA-DSS 2014). Both these data models contain a database structure specification, for example capturing existing utilities data, and additionally enable other useful data sets (e.g. environmental and dynamic organisational data).

Furthermore, the most important feature of the two models is the facilitation of inputs from databases of operational and maintenance data, for instance, databases regarding condition inspection reports or customer complaints.

The present section demonstrates that by understanding the factors that drive asset deterioration and highlighting the need to consistently link asset physical condition and system performance over the life of an asset, there is a very clear need to justify improving the frequency and resolution of asset data collection over current approaches used. New autonomous robotic inspection technologies that are currently emerging offer a pragmatic way forward to expand the asset condition and performance data sets that water utilities can collect (Thienen et al. 2018), and Mounce et al. (2021) conduct a detailed survey of the current landscape of emerging autonomous technologies in what is still a field in its infancy. Nevertheless, water utilities also need to collect environmental data (including data on other neighbouring buried assets systems) and link this into enhanced asset deterioration models.

6.0 Conclusions

The paper has shown that current condition assessment methods are underpinned by inspection technologies that locate and characterise discrete in-pipe defects. Such defect assessment methodologies are more mature in wastewater collection and drainage systems than water supply systems. Traditionally inspection technologies have been dominated by image based CCTV systems, although in the last few years significant improvement has occurred in commercially available inspection systems, resulting in a new range of both free swimming and tethered inspection systems focussed on better defect identification often to aid leakage detection, structural integrity and flow capacity assessment. Condition assessment approaches are still developing in water supply networks, due to even more limited access points and concerns over water safety with invasive techniques, however a range of defect inspection technologies are emerging. In both network types, condition assessment is limited by the cost, feasibility and disruption of the available methods. There are deterioration modelling approaches that attempt to utilise the available data, but they are all restricted by data availability and resolution issues. Even with improved inspection technologies, mentioned above it is still difficult to accurately evaluate how a defect develops with time. Hence the most common current deterioration modelling approaches still identify the risk of failure in asset cohorts rather than at individual assets, usually based on repair or maintenance data rather than inspection data. The paper has identified new idealised optimal data needs for both network types as well as their surrounding areas, and their relationships between asset condition, system performance and times to attain unacceptable levels of performance: wider range of factors that should be monitored and better temporal and spatial resolution. If these new data needs can be met then deterioration modelling approaches could be developed to identify individual assets with a high risk of failing to meet required levels of serviceability and hence limited investment be best targeted. The study also identified emerging robotic inspection technologies that are autonomous and capable of utilising a wider range of sensors to collect the required asset data at a much higher spatial and temporal resolution, and readily enable repeat inspection which is key to many deterioration modelling techniques. Such improved asset data sets combined with environmental data from other datasets could enable the development of much more reliable asset and system performance deterioration models, thus allowing for the first time focussed proactive repair and rehabilitation of assets.

Acknowledgements

This research is supported by UKRI EPSRC Programme grant EP/S016813/1 (Pipebots: www.pipebots.ac.uk).

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

8.0 References

Achim, D., Ghotb, F., and McManus, K. (2007). "Prediction of water pipe asset life using neural networks." *Journal of infrastructure systems*, 13(1), 26-30.

Ahmadi, M., Cherqui, F., De Massiac, J.-C., and Le Gauffre, P. (2014). "From sewer inspection programmes to rehabilitation needs: research and results related to data quality and availability with the support of numerical experiment." *European journal of environmental and civil engineering*, 18(10), 1145-1156.

Al-Barqawi, H., and Zayed, T. (2006). "Condition rating model for underground infrastructure sustainable water mains." *Journal of Performance of Constructed Facilities*, 20(2), 126-135.

Al-Barqawi, H., and Zayed, T. (2008). "Infrastructure management: Integrated AHP/ANN model to evaluate municipal water mains' performance." *Journal of Infrastructure Systems*, 14(4), 305-318.

Alvisi, S., and Franchini, M. (2014). "A heuristic procedure for the automatic creation of district metered areas in water distribution systems." *Urban Water Journal*, 11(2), 137-159.

Amaitik, N. M., and Amaitik, S. M. (2008). "Development of PCCP wire breaks prediction model using artificial neural networks." *Pipelines 2008: Pipeline Asset Management: Maximizing Performance of our Pipeline Infrastructure*, 1-11.

Ana, E., Bauwens, W., Pessemier, M., Thoeye, C., Smolders, S., Boonen, I., and De Gueldre, G. (2009). "An investigation of the factors influencing sewer structural deterioration." *Urban Water Journal*, 6(4), 303-312.

Ana, E., and Bauwens, W. (2010). "Modeling the structural deterioration of urban drainage pipes: the state-of-the-art in statistical methods." *Urban Water Journal*, 7(1), 47-59.

Aydogdu, M., and Firat, M. (2015). "Estimation of failure rate in water distribution network using fuzzy clustering and LS-SVM methods." *Water resources management*, 29(5), 1575-1590.

Babovic, V., Drecourt, J.-P., Keijzer, M., and Hansen, P. F. (2002). "A data mining approach to modelling of water supply assets." *Urban water*, 4(4), 401-414.

Bakry, I., Alzraiee, H., Kaddoura, K., El Masry, M., and Zayed, T. (2016). "Condition prediction for chemical grouting rehabilitation of sewer networks." *Journal of Performance of Constructed Facilities*, 30(6), 04016042.

Balekelayi, N., and Tesfamariam, S. (2019). "Statistical inference of sewer pipe deterioration using Bayesian geoadditive regression model." *Journal of Infrastructure Systems*, 25(3), 04019021.

Berardi, L., Giustolisi, O., Kapelan, Z., and Savic, D. (2008). "Development of pipe deterioration models for water distribution systems using EPR." *Journal of Hydroinformatics*, 10(2), 113-126.

Boxall, J., Saul, A., and Skipworth, P. (2004). "Modeling for hydraulic capacity." *Journal-American Water Works Association*, 96(4), 161-169.

Brevis, W., Susmel, L., and Boxall, J. (2015). "Investigating in-service failures of water pipes from a multiaxial notch fatigue point of view: A conceptual study." *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 229(7), 1240-1259.

Burn, S., Davis, P., and Gould, S. (2009). "Risk analysis for pipeline assets—the use of models for failure prediction in plastics pipelines." *Service Life Prediction of Polymeric Materials*, Springer, 183-204.

Caffoor, I. (2019). "Robotics and Autonomous Systems (RAS) for buried pipe infrastructure and water operations." *UK-RAS White Papers© UK-RAS*, T. E. G. EP/N010124/1, ed., University of Sheffield, Sheffiled, UK.

Caradot, N., Riechel, M., Fesneau, M., Hernandez, N., Torres, A., Sonnenberg, H., Eckert, E., Lengemann, N., Waschnewski, J., and Rouault, P. (2018). "Practical benchmarking of statistical and machine learning models for predicting the condition of sewer pipes in Berlin, Germany." *Journal of Hydroinformatics*, 20(5), 1131-1147.

Caradot, N., Sonnenberg, H., Kropp, I., Ringe, A., Denhez, S., Hartmann, A., and Rouault, P. (2017). "The relevance of sewer deterioration modelling to support asset management strategies." *Urban Water Journal*, 14(10), 1007-1015.

Carvalho, G., Amado, C., Brito, R. S., Coelho, S. T., and Leitão, J. P. (2018). "Analysing the importance of variables for sewer failure prediction." *Urban Water Journal*, 15(4), 338-345.

Christodoulou, S., Aslani, P., and Vanrenterghem, A. (2003). "A risk analysis framework for evaluating structural degradation of water mains in urban settings, using neurofuzzy systems and statistical modeling techniques." *Proc., World Water & Environmental Resources Congress 2003*, 1-9.

Chughtai, F., and Zayed, T. (2008). "Infrastructure condition prediction models for sustainable sewer pipelines." *Journal of Performance of Constructed Facilities*, 22(5), 333-341.

Chughtai, F., and Zayed, T. (2011). "Integrating WRc and CERIU condition assessment models and classification protocols for sewer pipelines." *Journal of Infrastructure Systems*, 17(3), 129-136.

Clair, A. M., and Sinha, S. (2012). "State-of-the-technology review on water pipe condition, deterioration and failure rate prediction models!" *Urban Water Journal*, 9(2), 85-112.

Clarke, B., Magee, D., Dimitrova, V., Cohn, A., Du, H., Mahesar, Q., Sadeghioon, A., Rogers, C., Gunn, D., Enwisle, D., Reeves, H., Stirling, R., and Glendinning, S. "A decision support system to proactively manage subsurface utilities." *Proc., Proc. of International Symposium for Next Generation Infrastructure (ISNGI), 11-13 Sep 2017*, 99-108.

Creighton, J. H. (2012). *A first course in probability models and statistical inference*, Springer Science & Business Media.

Cremer, F., van Deel, H.-G., Lehne, J., and Scholz, K. (2002). "Arbeitschilfen Abwasser Planung, Bau und Betrieb von abwassertechnischen Anlagen in Liegenschaften des Bundes." *KA WASSERWIRTSCHAFT ABWASSER*, 49(8), 1070-1077.

Davies, J., Clarke, B., Whiter, J., and Cunningham, R. (2001). "Factors influencing the structural deterioration and collapse of rigid sewer pipes." *Urban water*, 3(1-2), 73-89.

Davis, Paul; Burn, S.; Gould, S.; Cardy, M.; Tjandraatmadja, G. F.; Sadler, Paul A. (2007a) Long term performance prediction for PE pipes. [Project# 2975]. Denver, Colo.: AWWRF. http://hdl.handle.net/102.100.100/125548?index=1

Davis, P., Burn, S., Moglia, M., and Gould, S. (2007b). "A physical probabilistic model to predict failure rates in buried PVC pipelines." *Reliability Engineering System Safety*, 92(9), 1258-1266.

Davis, P., and Marlow, D. (2008). "Quantifying economic lifetime for asset management of large diameter pipelines." *American Water Works Association*, 100(7), 110-119.

Davis, P., Silva, D. D., Marlow, D., Moglia, M., Gould, S., and Burn, S. (2008). "Failure prediction and optimal scheduling of replacements in asbestos cement water pipes." *Journal of Water Supply: Research Technology—AQUA*, 57(4), 239-252.

De Silva, D., Moglia, M., Davis, P., and Burn, S. (2006). "Condition Assessment and Probabilistic Analysis to Estimate Failure Rates in Buried Pipelines." *Journal of Water Supply: Research and Technology-Aqua*, 55(3), 179-191.

Deb, A. K. (2002). *Prioritizing water main replacement and rehabilitation*, American Water Works Association.

Dehghan, A., McManus, K., and Gad, E. (2008a). "Statistical analysis of structural failures of water pipes." *Proc., Proceedings of the Institution of Civil Engineers-Water Management*, Thomas Telford Ltd, 207-214.

Dehghan, A., McManus, K. J., and Gad, E. F. (2008b). "Probabilistic failure prediction for deteriorating pipelines: Nonparametric approach." *Journal of performance of constructed facilities*, 22(1), 45-53.

Dirksen, J., Clemens, F., Korving, H., Cherqui, F., Le Gauffre, P., Ertl, T., Plihal, H., Müller, K., and Snaterse, C. (2013). "The consistency of visual sewer inspection data." *Structure and Infrastructure Engineering*, 9(3), 214-228.

Duchesne, S., Beardsell, G., Villeneuve, J. P., Toumbou, B., and Bouchard, K. (2013). "A survival analysis model for sewer pipe structural deterioration." *Computer-Aided Civil and Infrastructure Engineering*, 28(2), 146-160.

DWA. (2016). Zustandserfassung und -beurteilung von Entwässerungssystemen außerhalb von Gebäuden - Teil 7: Beurteilung der Umweltrelevanz des baulichen/betrieblichen Zustands [Condition assessment and classification of urban drainage systems outside of buildings]. Hennef, Germany: Deutsche Vereinigung für Wasserwirtschaft, Abwasser und Abfall e. V.

DWA. (2012). Leitfaden zur strategischen Sanierungsplanung von Entwässerungssystemen außerhalb von Gebäuden [Guideline on strategical rehabilitation planning of urban drainage systems outside of buildings]. Hennef, Germany: Deutsche Vereinigung für Wasserwirtschaft, Abwasser und Abfall e. V.

Egger, C., Scheidegger, A., Reichert, P., and Maurer, M. (2013). "Sewer deterioration modeling with condition data lacking historical records." *Water research*, 47(17), 6762-6779.

El Chanati, H., El-Abbasy, M. S., Mosleh, F., Senouci, A., Abouhamad, M., Gkountis, I., Zayed, T., and Al-Derham, H. (2016). "Multi-criteria decision making models for water pipelines." *Journal of Performance of Constructed Facilities*, 30(4), 04015090.

EN 752. (2008). Drain and sewer systems outside of buildings. CEN, Brussels.

EN 13508-2. (2011). Investigation and Assessment of Drain and Sewer Systems Outside Buildings–Part 2: Visual Inspection Coding System.

Fares, H., and Zayed, T. (2010). "Hierarchical fuzzy expert system for risk of failure of water mains." *Journal of Pipeline Systems Engineering Practice*, 1(1), 53-62.

Farshad, M. (2004). "Two new criteria for the service life prediction of plastics pipes." *Polymer Testing*, 23(8), 967-972.

Folkman, S. (2018). "Water main break rates in the USA and Canada: A comprehensive study." *Utah State University*, Buried Structures Laboratory.

Fox, S., Shepherd, W., Collins, R., and Boxall, J. (2016). "Experimental quantification of contaminant ingress into a buried leaking pipe during transient events." *Journal of Hydraulic Engineering*, 142(1), 04015036.

Fuentes, R., Chapman, T., Cook, M., Scanlan, J., Li, Z., and Richardson, R. C. (2017). "Briefing: UK-RAS white paper in robotics and autonomous systems for resilient infrastructure." *Proceedings of the Institution of Civil Engineers-Smart Infrastructure and Construction*, 170(3), 72-79.

Gedam, A., Mangulkar, S., and Gandhi, B. (2016). "Prediction of sewer pipe main condition using the linear regression approach." *Journal of Geoscience and Environment Protection*, 4(5), 100-105.

Geem, Z. W., Tseng, C.-L., Kim, J., and Bae, C. (2007). "Trenchless water pipe condition assessment using artificial neural network." *Pipelines 2007: Advances and Experiences with Trenchless Pipeline Projects*, 1-9.

Giustolisi, O., Laucelli, D., and Colombo, A. F. (2009). "Deterministic versus stochastic design of water distribution networks." *Journal of Water Resources Planning Management*, 135(2), 117-127.

Hahn, G. J., and Shapiro, S. S. (1994). *Statistical models in engineering*, Wiley, New York.

Harvey, R. R., and McBean, E. A. (2014). "Comparing the utility of decision trees and support vector machines when planning inspections of linear sewer infrastructure." *Journal of Hydroinformatics*, 16(6), 1265-1279.

Haykin, S. (2010). *Neural Networks and Learning Machines, 3/E*, Pearson Education India.

Hernández, N., Caradot, N., Sonnenberg, H., Rouault, P., and Torres, A. (2018). "Support tools to predict the critical structural condition of uninspected pipes for case studies of Germany and Colombia." *Water Practice & Technology*, 13(4), 794-802.

Hukka, J. J., and Katko, T. S. (2015). "Resilient asset management and governance for deteriorating water services infrastructure." *Procedia Economics and Finance*, 21, 112-119.

IKT. (2014). Bildreferenzkatalog - Private Abwasserleitungen (In German, Image Reference Catalog - Private Sewers), available at: https://www.ikt.de/blog/neuer-bildreferenzkatalog-zu-schaeden-an-privaten-abwasserleitungen/ (Accessed: 22 September 2021).

Ismail, A., and El-Shamy, A. (2009). "Engineering behaviour of soil materials on the corrosion of mild steel." *Applied clay science*, 42(3-4), 356-362.

Jones, D. F., Mirrazavi, S. K., and Tamiz, M. (2002). "Multi-objective meta-heuristics: An overview of the current state-of-the-art." *European journal of operational research*, 137(1), 1-9.

Jun, H. J., Park, J. K., and Bae, C. H. (2020). "Factors affecting steel water-transmission pipe failure and pipe-failure mechanisms." *Journal of Environmental Engineering*, 146(6), 04020034.

Kabir, G., Tesfamariam, S., Francisque, A., and Sadiq, R. (2015). "Evaluating risk of water mains failure using a Bayesian belief network model." *European Journal of Operational Research*, 240(1), 220-234.

Kabir, G., Balek, N. B. C., and Tesfamariam, S. (2018). "Sewer structural condition prediction integrating Bayesian model averaging with logistic regression." *Journal of Performance of Constructed Facilities*, 32(3), 04018019.

Kakoudakis, K., Behzadian, K., Farmani, R., and Butler, D. (2017). "Pipeline failure prediction in water distribution networks using evolutionary polynomial regression combined with K-means clustering." *Urban Water Journal*, 14(7), 737-742.

Khan, Z., Zayed, T., and Moselhi, O. (2010). "Structural condition assessment of sewer pipelines." *Journal of performance of constructed facilities*, 24(2), 170-179.

Khazraeializadeh, S., Gay, L. F., and Bayat, A. (2014). "Comparative analysis of sewer physical condition grading protocols for the City of Edmonton." *Canadian Journal of Civil Engineering*, 41(9), 811-818.

Kim, J., Bae, C., Woo, H., Kim, J., and Hong, S. (2007). "Assessment of residual tensile strength on cast iron pipes." *Pipelines 2007: Advances and Experiences with Trenchless Pipeline Projects*, 1-7.

Kleiner, Y., Nafi, A., and Rajani, B. (2010). "Planning renewal of water mains while considering deterioration, economies of scale and adjacent infrastructure." *Water Science Technology: Water Supply*, 10(6), 897-906.

Kleiner, Y., and Rajani, B. (1999). "Using limited data to assess future needs." *Journal-American Water Works Association*, 91(7), 47-61.

Kleiner, Y., and Rajani, B. (2001). "Comprehensive review of structural deterioration of water mains: statistical models." *Urban water*, 3(3), 131-150.

Kleiner, Y., and Rajani, B. (2002). "Forecasting variations and trends in water-main breaks." *Journal of infrastructure systems*, 8(4), 122-131.

Kleiner, Y., and Rajani, B. (2008). "Prioritising individual water mains for renewal." *Proc., World Environmental and Water Resources Congress 2008: Ahupua'A*, 1-10.

Kleiner, Y., Rajani, B., and Sadiq, R. (2005). *Risk management of large-diameter water transmission mains*, AWWA Research Foundation and American Water Works Association.

Kleiner, Y., Sadiq, R., and Rajani, B. (2004). "Modeling failure risk in buried pipes using fuzzy Markov deterioration process." *Pipeline Engineering and Construction: What's on the Horizon?*, 1-12.

Kley, G., Kropp, I., Schmidt, T., and Caradot, N. (2013). "SEMA D1. 1-Review of Available Technologies and Methodologies for Sewer Condition Evaluation." Berlin, Germany: Kompetenzzentrum Wasser Berlin.

Koo, D.-H., and Ariaratnam, S. T. (2006). "Innovative method for assessment of underground sewer pipe condition." *Automation in construction*, 15(4), 479-488.

Kutyłowska, M., and Hotloś, H. (2014). "Failure analysis of water supply system in the Polish city of Głogów." *Engineering Failure Analysis*, 41, 23-29.

Laakso, T., Kokkonen, T., Mellin, I., and Vahala, R. (2018). "Sewer condition prediction and analysis of explanatory factors." *Water*, 10(9), 1239.

Landau, L. J. (2012). *Concepts for neural networks: A survey*, Springer Science & Business Media.

Lawless, J. F. (2011). *Statistical models and methods for lifetime data*, John Wiley & Sons.

Le Gat, Y., and Eisenbeis, P. (2000). "Using maintenance records to forecast failures in water networks." *Urban water*, 2(3), 173-181.

Le Gat, Y. (2008). "Modelling the deterioration process of drainage pipelines." *Urban Water Journal*, 5(2), 97-106.

Le Gauffre, P., Joannis, C., Vasconcelos, E., Breysse, D., Gibello, C., and Desmulliez, J.-J. (2007). "Performance indicators and multicriteria decision support for sewer asset management." *Journal of Infrastructure Systems*, 13(2), 105-114.

Li, D., Cong, A., and Guo, S. (2019). "Sewer damage detection from imbalanced CCTV inspection data using deep convolutional neural networks with hierarchical classification." *Automation in Construction*, 101, 199-208.

Li, Z., Zhang, B., Wang, Y., Chen, F., Taib, R., Whiffin, V., and Wang, Y. (2014). "Water pipe condition assessment: a hierarchical beta process approach for sparse incident data." *Machine learning*, 95(1), 11-26.

Liu, Z., and Kleiner, Y. (2013). "State of the art review of inspection technologies for condition assessment of water pipes." *Measurement*, 46(1), 1-15.

Loganathan, G. V., Park, S., and Sherali, H. (2002). "Threshold break rate for pipeline replacement in water distribution systems." *Journal of water resources planning management*, 128(4), 271-279.

Lu, J. P., Davis, P., and Burn, L. (2003). "Lifetime prediction for ABS pipes subjected to combined pressure and deflection loading." *Polymer Engineering Science*, 43(2), 444-462.

Lubini, A. T., and Fuamba, M. (2011). "Modeling of the deterioration timeline of sewer systems." *Canadian Journal of Civil Engineering*, 38(12), 1381-1390.

Makar, J. (1999). "Diagnostic techniques for sewer systems." *Journal of Infrastructure Systems*, 5(2), 69-78.

Makropoulos, C., and Butler, D. (2005). "A neurofuzzy spatial decision support system for pipe replacement prioritisation." *Urban Water Journal*, 2(3), 141-150.

Mashford, J., Marlow, D., Tran, D., and May, R. (2011). "Prediction of sewer condition grade using support vector machines." *Journal of Computing in Civil Engineering*, 25(4), 283-290.

Malek Mohammadi, M., Najafi, M., Kermanshachi, S., Kaushal, V., and Serajiantehrani, R. (2020). "Factors Influencing the Condition of Sewer Pipes: State-of-the-Art Review." *Journal of Pipeline Systems Engineering and Practice*, 11(4), 03120002.

Marlow, D., Davis, P., Beale, D., Burn, S., and Urquhart, A. (2009). *Remaining asset life: A state of the art review*, Water Environment Research Foundation.

McDonald, S., Zhao, J., and Yehuda, K. (2001). "Guidelines for condition assessment and rehabilitation of large sewers." *Institute for Research in Construction National Research Council Canada, K1A0R6*.

Micevski, T., Kuczera, G., and Coombes, P. (2002). "Markov model for storm water pipe deterioration." *Journal of infrastructure systems*, 8(2), 49-56.

Moglia, M., Davis, P., and Burn, S. (2008). "Strong exploration of a cast iron pipe failure model." *Reliability Engineering System Safety*, 93(6), 885-896.

Mohammadi, M. M., Najafi, M., Tabesh, A., Riley, J., and Gruber, J. (2019). "Condition prediction of sanitary sewer pipes." *Pipelines 2019: Condition Assessment, Construction, and Rehabilitation*, American Society of Civil Engineers Reston, VA, 117-126.

Mounce, S. R., Shepherd, W. J., Boxall, J. B., Horoshenkov, K. V., and Boyle, J. H. (2021). "Autonomous robotics for water and sewer networks." *IAHR Hydrolink*, 2.

Najafi, M., and Kulandaivel, G. (2005). "Pipeline condition prediction using neural network models." *Pipelines 2005: Optimizing Pipeline Design, Operations, and Maintenance in Today's Economy*, 767-781.

Najjaran, H., Rajani, B., and Sadiq, R. (2004). "A fuzzy expert system for deterioration modeling of buried metallic pipes." *Proc., IEEE Annual Meeting of the Fuzzy Information, 2004. Processing NAFIPS'04.*, IEEE, 373-378.

Najjaran, H., Sadiq, R., and Rajani, B. (2006). "Fuzzy expert system to assess corrosion of cast/ductile iron pipes from backfill properties." *Computer-Aided Civil Infrastructure Engineering*, 21(1), 67-77.

NASSCO (2016). Pipeline Assessment Certification Program (PACP), Frederick, MD, USA: National Association of Sewer Service Companies.

National Archives (2008). The Water Supply and Sewerage Services (Customer Service Standards) Regulations, https://www.legislation.gov.uk/uksi/2008/594/schedules, accessed 28/09/21.

National Research Council Canada (2003). "Deterioration and inspection of water distribution systems, a best practice by the national guide to sustainable municipal infrastructure." *Federation of Canadian Municipalities and National Research Council* (1.1).

Nielsen, A. H., Vollertsen, J., Jensen, H. S., Wium-Andersen, T., and Hvitved-Jacobsen, T. (2008). "Influence of pipe material and surfaces on sulfide related odor and corrosion in sewers." *Water Research*, 42(15), 4206-4214.

Oliveira, D., Guo, W., Soibelman, L., and Garrett, J., James H (2007). "Spatial Data Management and Analysis in Sewer Systems' Condition Assessment: an Overview." *Computing in Civil Engineering (2007)*, 391-398.

Ormsby, C. (2009). "A framework for estimating the total cost of buried municipal infrastructure renewal projects." MS Thesis, Department of Civil Engineering and Applied Mechanics, McGill University, Montreal, CN.

Osman, H., and Bainbridge, K. (2011). "Comparison of statistical deterioration models for water distribution networks." *Journal of Performance of Constructed Facilities*, 25(3), 259-266.

Park, S. W., and Loganathan, G. (2002). "Methodology for economically optimal replacement of pipes in water distribution systems: 1. Theory." *KSCE Journal of Civil engineering*, 6(4), 539-543.

Parrott, C., Dodd, T. J., Boxall, J., and Horoshenkov, K. (2020). "Simulation of the behavior of biologically-inspired swarm robots for the autonomous inspection of buried pipes." *Tunnelling and Underground Space Technology*, 101, 103356.

Pelletier, G., Mailhot, A., and Villeneuve, J.-P. (2003). "Modeling water pipe breaks—Three case studies." *Journal of water resources planning management*, 129(2), 115-123.

Poulton, M., Le Gat, Y., and Brémond, B. (2009). "The impact of pipe segment length on break predictions in water distribution systems." *Strategic Asset Management of Water Supply Wastewater Infrastructures*, 419.

Rajani, B. (2000). *Investigation of grey cast iron water mains to develop a methodology for estimating service life*, American Water Works Association.

Rajani, B., and Kleiner, Y. (2001). "Comprehensive review of structural deterioration of water mains: physically based models." *Urban water*, 3(3), 151-164.

Rajani, B., and Makar, J. (2000). "A methodology to estimate remaining service life of grey cast iron water mains." *Canadian Journal of Civil Engineering*, 27(6), 1259-1272.

Rajani, B., and Tesfamariam, S. (2007). "Estimating time to failure of cast-iron water mains." *Proceedings of the Institution of Civil Engineers-Water Management*, 160(2), 83-88.

Rajeev, P., Kodikara, J., Robert, D., Zeman, P., and Rajani, B. (2014). "Factors contributing to large diameter water pipe failure." *Water asset management international*, 10(3), 9-14.

Reed, C., Robinson, A. J., and Smart, D. (2006). *Potential techniques for the assessment of joints in water distribution pipelines*, Amer Water Works Assn

Rezaei, H., Ryan, B., and Stoianov, I. (2015). "Pipe failure analysis and impact of dynamic hydraulic conditions in water supply networks." *Procedia Engineering*, 119, 253-262.

RIONED (2017) Gegevenswoordenboek Stedelijk Water [Data Dictionary Urban Water]. GWSW, Ede, The Netherlands. https://www.riool.net/gegevenswoordenboek-stedelijk-water.

Rogers, C., Metje, N., Makana, L., Atkins, P., Hayati, F., Rustighi, E., Al-Khoury, A., Pennock, S., Jenks, H., Boxall, J., Collins, R., Zhu, J., Mills, R., Dwyer-Joyce, R., Anderson, S., and Dodd, T. (2017). "Assessing the Underworld – Understanding the Context for Engineering the Next Generation Infrastructure." *Proc., Proc. of International Symposium for Next Generation Infrastructure (ISNGI), 11-13 Sep 2017*, 341-350.

Rokstad, M., and Ugarelli, R. (2016). "Improving the benefits of sewer condition deterioration modelling through information content analysis." *Water Science and Technology*, 74(10), 2270-2279.

Sadiq, R., Rajani, B., and Kleiner, Y. (2004). "Fuzzy-based method to evaluate soil corrosivity for prediction of water main deterioration." *Journal of infrastructure systems*, 10(4), 149-156.

Salman, B., and Salem, O. (2012). "Modeling failure of wastewater collection lines using various section-level regression models." *Journal of Infrastructure Systems*, 18(2), 146-154.

Savic, D. A. (2009). "The use of data-driven methodologies for prediction of water and wastewater asset failures." *Risk Management of Water Supply and Sanitation Systems*, Springer, 181-190.

Scheidegger, A., Leitão, J. P., and Scholten, L. (2015). "Statistical failure models for water distribution pipes–A review from a unified perspective." *Water research*, 83, 237-247.

Seica, M. V., and Packer, J. A. (2004). "Finite element evaluation of the remaining mechanical strength of deteriorated cast iron pipes." *J. Eng. Mater. Technol.*, 126(1), 95-102.

Seica, M. V., and Packer, J. A. (2006). "Simplified numerical method to evaluate the mechanical strength of cast iron water pipes." *Journal of infrastructure systems*, 12(1), 60-67.

Shirzad, A., Tabesh, M., and Farmani, R. (2014). "A comparison between performance of support vector regression and artificial neural network in prediction of pipe burst rate in water distribution networks." *KSCE Journal of Civil Engineering*, 18(4), 941-948.

Sivanandam, S., Sumathi, S., and Deepa, S. (2007). *Introduction to fuzzy logic using MATLAB*, Springer.
Sousa, V., Matos, J. P., and Matias, N. (2014). "Evaluation of artificial intelligence tool performance and uncertainty for predicting sewer structural condition." *Automation in Construction*, 44, 84-91.

Tesfamariam, S., Rajani, B., and Sadiq, R. (2006). "Possibilistic approach for consideration of uncertainties to estimate structural capacity of ageing cast iron water mains." *Canadian Journal of Civil Engineering*, 33(8), 1050-1064.

Thienen, P., Bergmans, B., and Diemel, R. (2018). "Advances in Development and Testing of a System of Autonomous Inspection Robots for Drinking Water Distribution Systems." *Proc., WDSA/CCWI Joint Conference Proceedings*.

Tran, D., Ng, A., Perera, B. J. C., Burn, S., and Davis, P. (2006). "Application of probabilistic neural networks in modelling structural deterioration of stormwater pipes." *Urban Water Journal*, 3(3), 175-184.

Tran, D., Perera, B. C., and Ng, A. (2009). "Comparison of structural deterioration models for stormwater drainage pipes." *Computer-Aided Civil and Infrastructure Engineering*, 24(2), 145-156.

Tran, D. H., Ng, A., and Perera, B. J. C. (2007). "Neural networks deterioration models for serviceability condition of buried stormwater pipes." *Engineering Applications of Artificial Intelligence*, 20(8), 1144-1151.

Tscheikner-Gratl, F., Caradot, N., Cherqui, F., Leitão, J. P., Ahmadi, M., Langeveld, J. G., Le Gat, Y., Scholten, L., Roghani, B., and Rodríguez, J. P. (2019). "Sewer asset management–state of the art and research needs." *Urban Water Journal*, 16(9), 662-675.

USEPA (2002). "Deteriorating Buried Infrastructure Management Challenges and Strategies." U. S. E. P. A. (USEPA), ed., American Water Works Service Co. Inc., Engineering Department, Washington DC.

van Riel, W., Langeveld, J., Herder, P., and Clemens, F. (2014). "Intuition and information in decision-making for sewer asset management." *Urban Water Journal*, 11(6), 506-518.

van Riel, W., van Bueren, E., Langeveld, J., Herder, P., and Clemens, F. (2016). "Decision-making for sewer asset management: Theory and practice." *Urban Water Journal*, 13(1), 57-68.

Vanrenterghem-Raven, A. (2007). "Risk factors of structural degradation of an urban water distribution system." *Journal of infrastructure systems*, 13(1), 55-64.

VSA-DSS (2014). "Datenstruktur Siedlungsentwässerung [Data Structure Urban Water]."

Wang, C.-w., Niu, Z.-g., Jia, H., and Zhang, H.-w. (2010). "An assessment model of water pipe condition using Bayesian inference." *Journal of Zhejiang University-SCIENCE A*, 11(7), 495-504.

Wang, Y., Zayed, T., and Moselhi, O. (2009). "Prediction models for annual break rates of water mains." *Journal of performance of constructed facilities*, 23(1), 47-54.

Wasson, C. S. (2015). *System engineering analysis, design, and development: Concepts, principles, and practices*, John Wiley & Sons.

Watson, T., Christian, C., Mason, A., Smith, M., and Meyer, R. (2004). "Bayesian-based pipe failure model." *Journal of Hydroinformatics*, 6(4), 259-264.

Wirahadikusumah, R., Abraham, D., and Iseley, T. (2001). "Challenging issues in modeling deterioration of combined sewers." *Journal of infrastructure systems*, 7(2), 77-84.

Wood, A., and Lence, B. J. (2009). "Using water main break data to improve asset management for small and medium utilities: District of Maple Ridge, BC." *Journal of Infrastructure Systems*, 15(2), 111-119.

WRc. (2013). Manual of Sewer Condition Classification. 5th Revised Edition. WRc Publications.

WRc. (2021). Sewerage Risk Manual. Available at: http://srm.wrcplc.co.uk/home.aspx [Accessed 22/09/2021].

Younis, R., Knight, M., Kleiner, Y., Matthews, J., and Jung, J. (2015). "Drinking water pipelines defect coding system." *Pipelines 2015*, 1110-1124.

Zhou, Y., Vairavamoorthy, K., and Grimshaw, F. (2009). "Development of a fuzzy based pipe condition assessment model using PROMETHEE." *Proc., World Environmental and Water Resources Congress 2009: Great Rivers*, 1-10.

List of Figure Captions

Figure 1: Schematic describing the factors which can control the deterioration of buried water supply pipes

Figure 2: Optimal dataset required for key asset characteristics of water and wastewater networks

Figure 3: Optimal environmental dataset for buried assets of water and wastewater networks

Figure 4: Conceptual relationships between asset condition, system performance and times to attain unacceptable levels of performance

Tables

Table 1: Current protocols that are used to evaluate the condition and performance of a sewer pipe, modified after Tscheikner-Gratl et al. (2019)

Category	Description	Examples of Parameters Used	References
Complete	An all-inclusive evaluation of the pipes condition to inform rehabilitation strategies founded upon the apparent defects or merging the various categories described below	Connections, start and end invert elevation, installation method, joint type, pipe length, pipe size and shape, pipe slope, sewer age, sewer depth, sewer pipe material.	Chughtai and Zayed 2011; EN 752 2008; Kley et al. 2013; McDonald et al. 2001; WRc 2013
Operational	Defect classification that results in operational interventions for the pipe in question	Roots, attached deposits, ingress of soil, obstacles, infiltration, exfiltration, previous maintenance, burst history, blockages, debris, flow velocity, hydraulic condition, sewer function, sediment deposit level, surcharge, and vermin.	Ahmadi et al. 2014; ATV, M 1999; Chughtai and Zayed 2011; EN 752 2008; EN 13508-2 2011; McDonald et al. 2001; NASSCO 2016; WRc 2013
Structural	Defect classification of the physical pipe condition which takes into account defects that cause deterioration and failure of the pipe	Deformation, fissure/crack, break/collapse, defective brickwork or masonry, missing mortar, surface damage, intruding connection, defective connection, intruding sealing material, displaced joint, lining observations, defective repair, weld failure, porous pipe.	Ahmadi et al. 2014; Chughtai and Zayed 2011; EN 752 2008; Khazraeializadeh et al. 2014; Kley et al. 2013; McDonald et al. 2001; WRc 2013
Reliability (structural)	Evaluation of the structural condition with regard to long term planning, thus establishing the residual service life and structural reliability metrics of sewers	Type of waste water network, character of sewerage, water protection area, relative position to groundwater, soil type, circumferential position, position on joint.	DWA-Themen T4 2012; Kley et al. 2013
Environmental Impact	Evaluation of defects that produce pollution of water within the hydrological cycle	Backfill type, bedding material, ground movement, groundwater level, pH, road type, root interference, soil corrosively, soil fracture potential, soil moisture, soil type, sulphate soil, and surface type.	DWA-M 149-7 2016; EN 752 2008
Hydraulic or serviceability	Evaluation of defects that will produce more turbulent flow energy losses	Leaktightness (type of joint, hydraulic load, position of groundwater), stability (depth of cover, soil type), operational safety (hydraulic load, depth of cover).	Ahmadi et al. 2014; Cremer et al. 2002; EN 752 2008; Micevski et al. 2002; Tscheikner-Gratl et al. 2019
Gradual failures	The effect of defects on network operations	Infiltration, exfiltration, blockage, silting, material corrosion.	Ahmadi et al. 2014; Kley et al. 2013; Le Gauffre et al. 2007

Table 2: Deterioration modelling approaches, their predictive focus and relative data needs - summary of literature review

Deterministic Models			Statistical Models			Probabilistic Models			Artificial Neural Networks			Fuzzy Logic Models			Heuristic Models		
Prediction Type	***References***	***DR***	***Prediction Type***	***References***	***DR***	***Prediction Type***	***References***	***DR***	***Prediction Type***	***References***	***DR***	***Prediction Type***	***References***	***DR***	***Prediction Type***	***References***	***DR***
Review of deterministic models	*37 (WS)*	↑	*Review of statistical models*	*22 (WS)*	↑	*Failure rates*	*10 (WS), 13 (WS), 15 (WS), 16 (WS), 30 (WS & WW), 73 (WW)*	↓	*Pipe failure*	*1 (WS), 8 (WS), 70 (WW), 72 (WW)*	↑	*Deterioration rates*	*24 (WS), 25 (WS), 31 (WS), 32 (WS), 40 (WS)*	↓	*Break rates*	*21 (WS)*	↔
Remaining service life	*36 (WS), 38 (WS)*	↑	*Failure rates*	*6 (WS), 26 (WS), 41 (WS & WW), 68 (WW)*	↔	*Lifetime*	*10 (WS), 11 (WS)*	↓	*Condition rating*	*2 (WS), 19 (WS), 59 (WW), 67 (WW), 69 (WW)*	↑	*Vulnerability rates*	*29 (WS)*	↓	*Failure rates*	*48 (WS & WW)*	↔
Prioritising replacement	*14 (WS)*	↑	*Optimal replacement*	*27 (WS), 33 (WS), 56 (WW)*	↔	*Deterioration rate*	*62 (WW), 65 (WW)*	↓	*PCCP wire breaks*	*4 (WS)*	↑	*Failure rates*	*39 (WS), 44 (WS)*	↓	*Condition rating*	*2 (WS), 3 (WS), 50 (WS), 64 (WW)*	↔
Risks of pipe burst	*5 (WS)*	↑	*Break rates*	*23 (WS), 34 (WS), 35 (WS), 45 (WS), 46 (WS), 49 (WS)*	↔				*Review of neural networks deterioration models*	*71 (WW)*	↑	*Risk of failure*	*17 (WS)*	↓	*Optimal Replacement*	*57 (WW)*	↔
Lifetime prediction	*28 (WS)*	↑	*Deterioration rates*	*47 (WS), 51 (WW), 53 (WW), 54 (WW), 55 (WW), 58 (WW), 60 (WW), 63 (WW)*	↔												
Service life prediction	*18 (WS & WW)*	↑	*Condition rating*	*52 (WW), 61 (WW), 66 (WW)*	↔												
Strength	*42 (WS), 43 (WS)*	↑															
Residual life	*20 (WS)*	↑															
Time to failure	*12 (WS)*	↑															
Lifetime	*7 (WS & WW), 9 (WS)*	↑															

(1) Achim et al. (2007), (2) Al-Barqawi and Zayed (2006), (3) Al-Barqawi and Zayed (2008), (4) Amaitik and Amaitik (2008), (5) Babovic et al. (2002), (6) Berardi et al. (2008), (7) Burn et al. (2009), (8) Christodoulou et al. (2003), (9) Davis et al. (2007a), (10) Davis et al. (2007b), (11) Davis and Marlow (2008), (12) Davis et al. (2008), (13) De Silva et al. (2006), (14) Deb (2002), (15) Dehghan et al. (2008a), (16) Dehghan et al. (2008b), (17) Fares and Zayed (2010), (18) Farshad (2004), (19) Geem et al. (2007), (20) Kim et al. (2007), (21) Kleiner and Rajani (1999), (22) Kleiner and Rajani (2001), (23) Kleiner and Rajani (2008), (24) Kleiner et al. (2005), (25) Kleiner et al. (2004), (26) Le Gat and Eisenbeis (2000), (27) Loganathan et al. (2002), (28) Lu et al. (2003), (29) Makropoulos and Butler (2005), (30) Moglia et al. (2008), (31) Najjaran et al. (2004), (32) Najjaran et al. (2006), (33) Park and Loganathan (2002), (34) Pelletier et al. (2003), (35) Poulton et al. (2009), (36) Rajani (2000), (37) Rajani and Kleiner (2001), (38) Rajani and Makar (2000), (39) Rajani and Tesfamariam (2007), (40) Sadiq et al. (2004), (41) Savic (2009), (42) Seica and Packer (2004), (43) Seica and Packer (2006), (44) Tesfamariam et al. (2006), (45) Vanrenterghem-Raven (2007), (47) Wang et al. (2010), (46) Wang et al. (2009), (48) Watson et al. (2004), (49) Wood and Lence (2009), (50) Zhou et al. (2009), (51) Ana et al. (2009), (52) Bakry et al. (2016), (53) Balekelayi and Tesfamariam (2019), (54) Chughtai and Zayed (2008), (55) Davies et al. (2001), (56) Gedam et al. (2016), (57) Harvey and McBean (2014), (58) Kabir et al. (2018), (59) Khan et al. (2010), (60) Koo and Ariaratnam (2006), (61) Laakso et al. (2018), (62) Le Gat (2008), (63) Lubini and Fuamba (2011), (64) Mashford et al. (2011), (65) Micevski et al. (2002), (66) Mohammadi et al. (2019), (67) Najafi and Kulandaivel (2005), (68) Salman and Salem (2012), (69) Sousa et al. (2014), (70) Tran et al. (2006), (71) Tran et al. (2009), (72) Tran et al. (2007), (73) Wirahadikusumah et al. (2001).

DR: Data Requirements
Key: ↑ High, ↔ Medium, ↓ Low
Usages: (**WS**) Water Supply, (**WW**) Wastewater

Table 3: Factors that cause deterioration of water pipelines – summary of literature review

Category (Index)	***Deterioration elements***	***Description***	***References***
I	***Operational Components***		
(C1)	*Water velocity*	*Influences travel times, so chemical and bioprocesses, and sediment processes such as scouring and blockages*	*6, 10*
(C2)	*Water and wastewater quality*	*Substances within the water pipe flow could generate corrosion on the internal pipe wall surface*	*6, 10*
(C3)	*Hydraulic pressure - level and fluctuation*	*The internal stress of the pipe is directly proportional to the hydraulic pressure*	*4, 6, 10*
II	***Environmental Components***		
(C4)	*Groundwater properties*	*Corrosion of the pipe is influenced by properties within the groundwater*	*1, 5*
(C5)	*Infiltration*	*Contributes to the rate of deterioration - soil movement leading to increased soil-pipe interaction*	*6, 8*
(C6)	*Seismic activity*	*Seismic activity amplifies the stress and strain in the pipelines due to ground shaking, ground rupture, landslides and liquefaction*	*1, 6, 9*
(C7)	*Level of soil linked corrosion processes*	*Soil that is corrosive will amplify the rate of deterioration of the pipe from the external surface*	*4, 5, 6, 9, 13*
(C8)	*Freezing index*	*The stress and strain on the pipe can be increased by physical loading from frost, which alters allowable design limits*	*5, 6, 8, 9*
III	***Physical Components***		
(C9)	*Defective installation techniques and manufacturing faults*	*The structural integrity of the pipe and its joints can be reduced by factors such as poor installation practice and manufacturing faults*	*4*
(C10)	*Pipe diameter*	*Large diameter pipes are less prone to deterioration compared to smaller diameter pipes - due to pipe wall thickness and less impacting pipe-soil interaction*	*1, 2, 3, 4, 6, 7, 11, 12*
(C11)	*Pipe length*	*The longer the pipe, the higher probability of defect occurrence and higher costs*	*1, 2, 3, 6, 7, 11, 12*
(C12)	*Pipe wall thickness*	*Thicker pipe walls have greater strength and resistance to corrosion related structural failure*	*4, 6, 11, 12*
(C13)	*Pipe age*	*Older pipes tend to experience a higher deterioration rate - this is a reflection of higher probability of encountering dynamic and operational factors*	*1, 2, 3, 4, 6, 7, 8, 11, 12*
(C14)	*Pipe material*	*Material properties dictate the manner in which failure can occur as well as vulnerability to corrosion*	*3, 4, 6, 8, 11, 12, 13*
(C15)	*Incidence coating and lining*	*Pipe strength and corrosion resistance is increased by appropriate coating and lining*	*9*
(C16)	*Type of joints*	*Depending on the material of the pipe (e.g. steel, cast iron, ductile iron, PVC, RC, AC, PC etc.), some of the joint types (e.g. welded, rubber, lead, leadite, heat fused etc.) experience premature failure due to e.g. joint displacements, traverse stresses on joint, defective joints, faulty installation, brittle failure, connection failure, joint burst, age of joint/material degradation, expansion of joint material, vacuum collapse due to lower pressure ratings, material fatigue, joint gap, joint deflection etc.*	*4, 12, 14, 15, 16, 17, 18, 19, 20*

(1) Ana and Bauwens (2010), (2) Aydogdu and Firat (2015), (3) Berardi et al. (2008), (4) Folkman (2018), (5) Ismail and El-Shamy (2009), (6) Kabir et al. (2015), (7) Kakoudakis et al. (2017), (8) Kleiner et al. (2010), (9) Kutyłowska and Hotloś (2014), (10) Shirzad et al. (2014), (11) Clair and Sinha (2012), (12) Wang et al. (2009), (13) Nielsen et al. (2008), (14) Al-Barqawi and Zayed (2006), (15) Liu, et al. (2012), (16) Reed et al. (2006), (17) National Research Council Canada (2003), (18) Rezaei et al. (2015), (19) USEPA (2002), (20) Rajani et al. (1996).

Figure 1: Schematic describing the factors which can control the deterioration of buried water supply pipes. Dynamic factors change over time and are often related to the

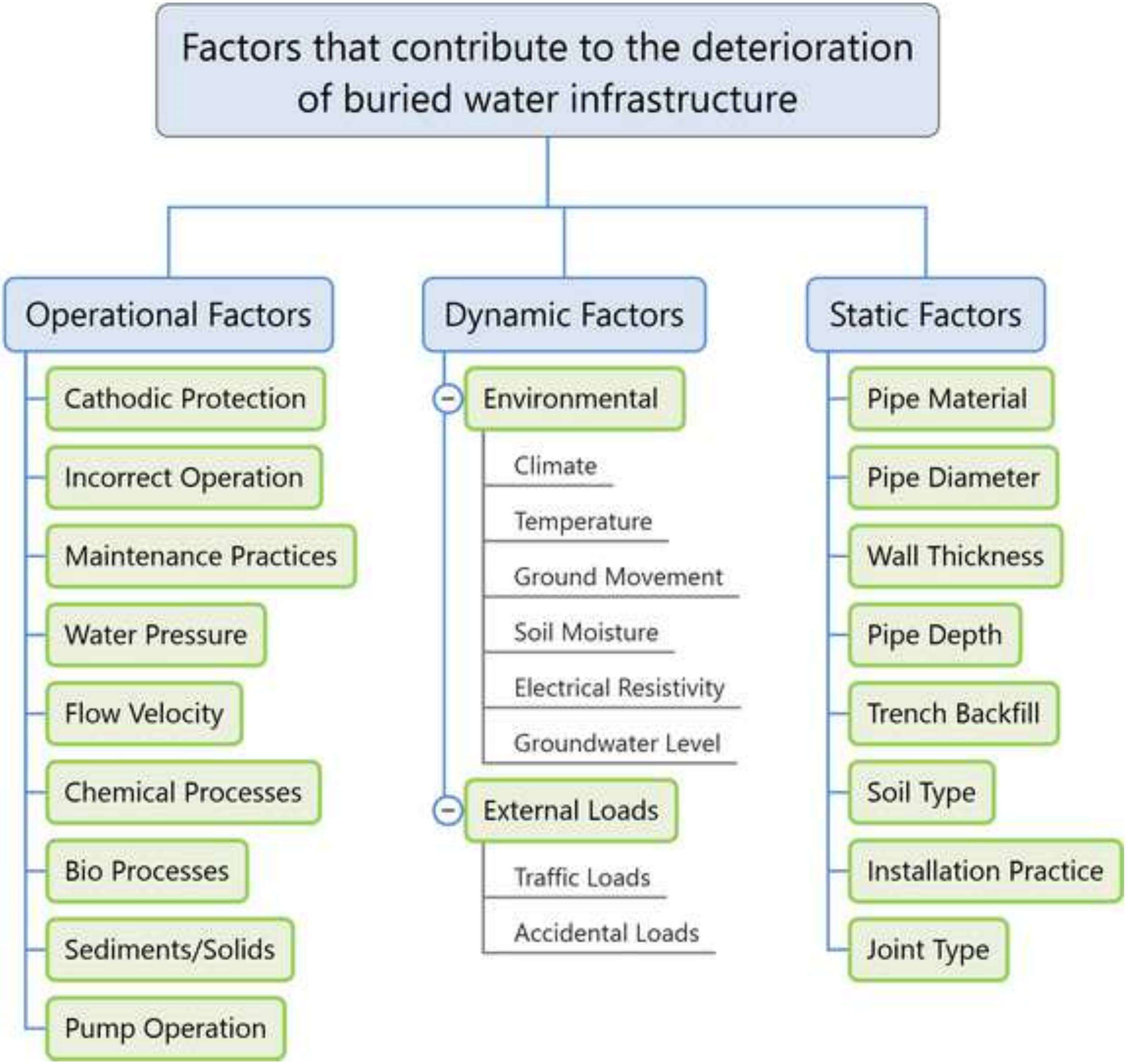

Figure 2 :Optimal dataset required for key asset characteristics of water and wastewater networks

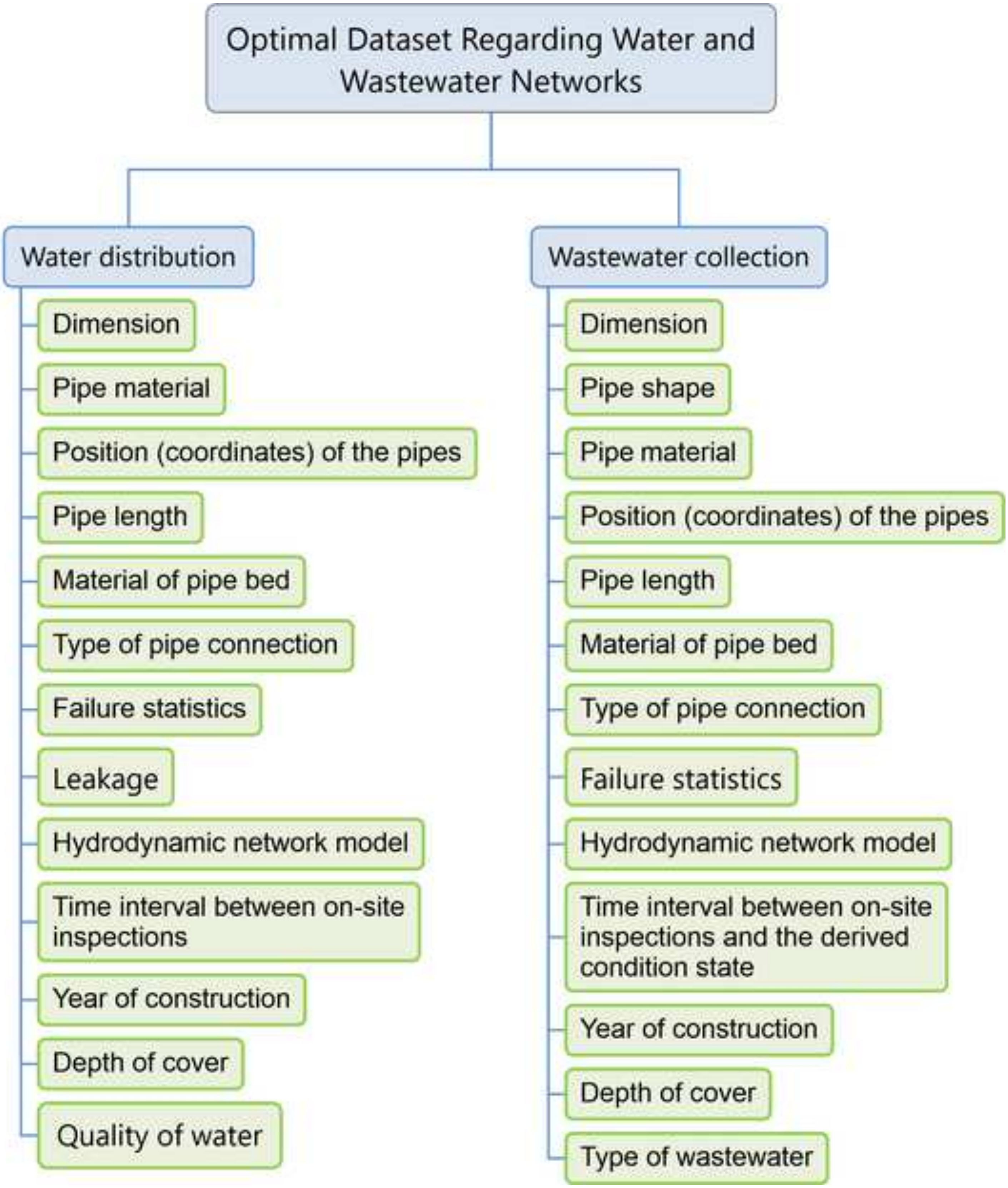

Figure 3: Optimal environmental dataset for buried assets of water and wastewater networks

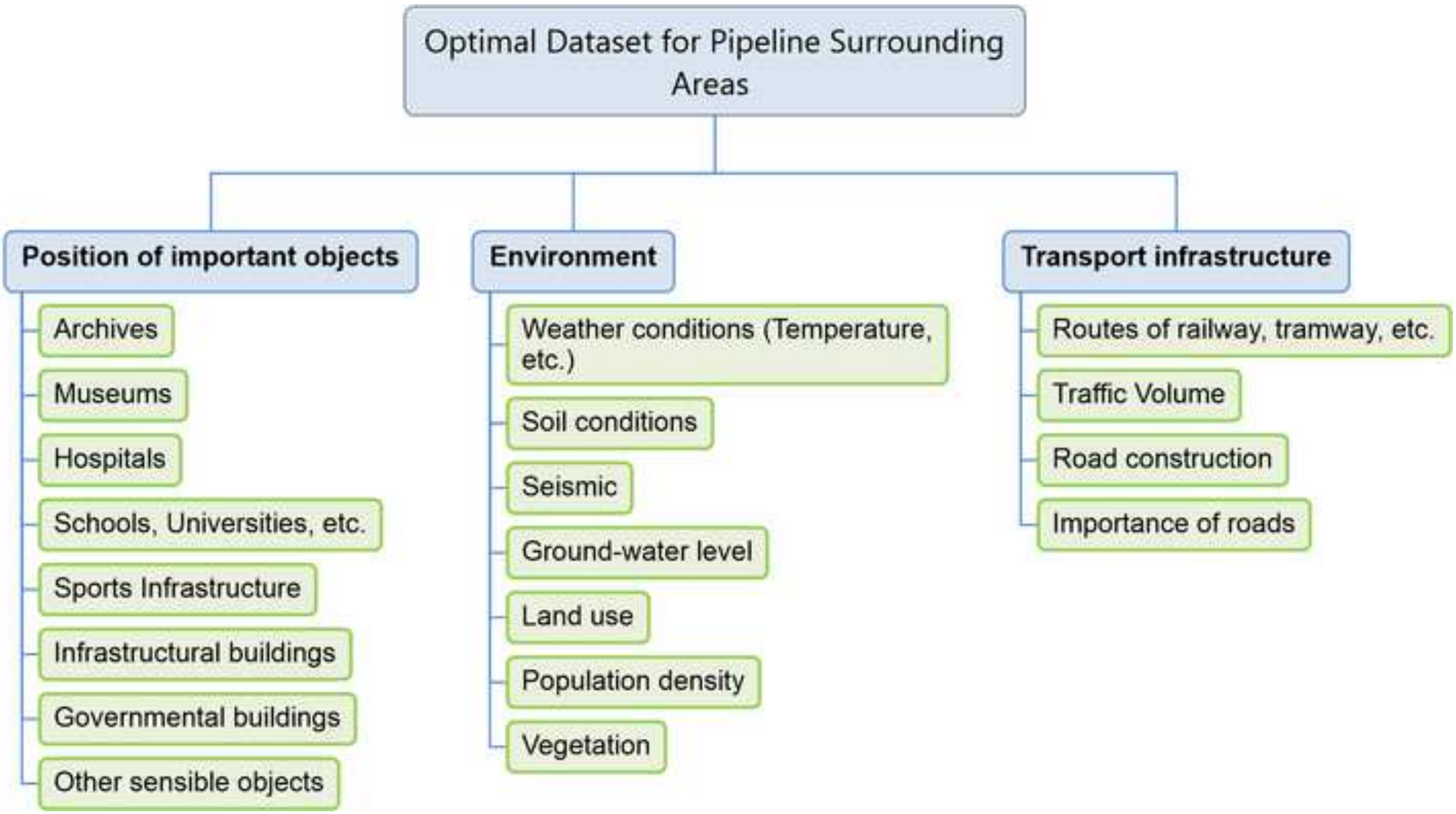

Figure 4: Conceptual relationships between asset condition, system performance and times to attain unacceptable levels of performance