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Future inspection and deterioration prediction capabilities for buried distributed water infrastructure

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[Link to publication on Research at Birmingham portal](#)

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

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42   **Abstract:** This paper examines the role for pipe deterioration prediction approaches for optimising

43   maintenance, repair and rehabilitation of buried water supply, wastewater collection and drainage networks.

44   It is appreciated that there are other ancillary assets within water supply and wastewater collection and

45   drainage networks, but these were not considered in this paper. Currently there are a range of asset condition

46   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.

74   From this simple introduction, it can be argued that these water infrastructures are the lifeblood of cities

75   across the world, and failure to function adequately and deliver their services can lead to considerable social,

76   economic and environmental losses (Ana and Bauwens 2010). Potable water pipe infrastructures are often

77   stated to have a service life of 50-120 years (Ormsby 2009; Li et al. 2014), although many pipelines currently

78   in operation in the UK and other countries greatly exceed this upper limit, hence failures can be expected.

79   Makar et al. (2020) contend that the cost of such failures could amount to £thousands to £millions in repair

80   and replacement costs, and collateral damage to the overlying (roads in towns and cities) and adjacent buried

81   infrastructures. To these direct costs, that can range up to 80% of what utilities spend (Hukka and Katko 2015),

82   should be added the multiple forms of social and environmental costs caused by disruption to urban systems

83   and damage to the natural environment. This simply serves to emphasise the need to understand pipe

84   condition and how it impacts on system performance, intervening using an array of asset management

85   practices before failures occur.

86   The chief concern in infrastructure asset management is the maintenance of service of an adequate quality

87   without (undue or lengthy) disruption to service in an effective and cost efficient manner. In many countries

88   water supply, wastewater collection and drainage networks are required to deliver defined levels of service,

89   for example in the UK these networks should not exceed a particular number of service supply interruptions

90   or number of flooding incidents (National Archives 2008). Network operators consequently try to link the

91   ability of their infrastructure to meet these defined levels of service (system performance) with the physical

92   characteristics of individual assets (condition); this in turn enables assessment of asset condition to inform

93   robust decision-making on where and when to repair, rehabilitate or replace vulnerable assets. Deterioration

94   models inevitably have a role to play in this decision-making, and yet all this relies upon comprehensive and

95   accurate condition assessment.

96   The goal of buried pipeline condition assessment is commonly too narrowly-focussed: buried pipelines only

97   perform structurally if adequately supported by the ground, and hence it is the complete pipe-soil system that

98   needs to be assessed and understood. Extending this argument further, it is an appreciation of the complete

99   context in which a pipeline exists that should be sought, leading to the model advocated by Rogers et al. (2017)

100   of three interdependent infrastructures in the street: the buried infrastructure (water and sewer networks),

101   the surface infrastructure (road structures) and the geotechnical infrastructure (the ground). Treating the

102   ground as an infrastructure enables helpful performance insights, such as the application of deterioration

103   models to the ground. Conversely, without an understanding of the competence of ground support it is

104   impossible to fully appreciate the consequences of defect identification and mapping.

105   At present sewers and drainage pipelines, and occasionally water supply pipelines, are inspected internally

106   using, for example, cameras or sensors mounted on a tethered platform or sensor platforms inserted into the

107   network, that advect with the flow and are then retrieved after a certain period of time to identify individual

108   defects and so as determine asset condition. Asset condition is then often ranked based on the number and/or

109   severity of individual defects. Crucially, this process does not include an assessment of whether the asset is

110   likely to meet its required service levels and nor does it assess the surrounding context other than by

111   implication in some cases (e.g. a displaced joint might indicate exfiltration and a loss of ground support).

112   Moreover, condition assessment of buried water infrastructure is usually carried out with limited resources

113   and with a piecemeal characterisation and inventory of related systems' features (Oliveira et al., 2007), often

114   resulting in only a small part of any network being regularly and effectively inspected (Tscheikner-Gratl et al.

115   2019). This results in a far from comprehensive assessment of the asset base, but more like a series of spot

116   checks on lengths of the pipeline network for which there is a cause for concern or an appreciation that failure

117   would have significant consequences.

118   Deterioration processes relate to both structural and functional deterioration. Structural deterioration

119   processes operate at different rates depending on many contextual features and the various kinds of stresses

120   that occur (Rajani and Kleiner 2001), and thus a spot check in time, even if allied to a deterioration model,

121   provides no assurance of condition understanding significantly into the future. Functional deterioration - the

122   failure to meet functional requirements such as intermittent blockages in sewers or drainage pipes causing

123   flooding or compromised water quality in damaged water pipes (for example contaminant ingress, Fox et al.

124   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

151 'fitness-for-purpose' and 'fitness-for-service' procedures (Younis et al. 2015), the majority of which still

152 underlie many of today's standard asset condition measurement practices in water and sewerage companies.

153 For example, the UK's Water Research Centre (WRc) published the first edition of the Manual of Sewer

154 Condition Classification (MoSCC) in 1980 and this framework is currently in its fifth edition (WRc 2013). There

155 are also similar documents and standards for pipe inspection and classification of defects, and estimation of

156 condition in sewers across the world, including for example EN 13508-2 (2011) in Europe, and IKT (2014) in

157 Germany. The Sewerage Rehabilitation Manual, now re-named Sewerage Risk Management (WRc 2021), was

158 first published in 1983 building on MoSCC to develop an objective based methodology for rehabilitating

159 sewerage networks principally based on observed defects and inferred asset condition. This approach has

160 been refined as system performance requirements changed over time and a more risk based approach became

161 appropriate.

162 Conversely, no regular standardised condition classification system is in operation to date for water supply

163 pipelines. A plethora of reasons have factored into this situation, comprising but not limited to inadequate

164 funding for water utilities, high inspection costs, the density and complexity of water distribution systems, risk

165 of water contamination, being located underground with limited (if any) access points, pipes made of assorted

166 materials, which by consequence led to use of a wide range inspection technologies and condition assessment

167 schemes (Rajani and Kleiner 2001; Li et al. 2014). To-date, limited work has been conducted on synthesising

168 the assessment of different types of defects and by consequence the resulting pipe condition in water

169 distribution pipes, although attempts have been made to develop a framework for an accepted standardised

170 defect classification system for water distribution pipelines (Younis et al. 2015), where recent funded WRF

171 work has attempted to develop a standardised condition classification for water supply systems, but currently

172 more development is needed. The main reason for no standard condition classification system is the enhanced

173 difficulty in collecting defect data in comparison to sewer systems. It is difficult to insert inspection systems in

174 a pressurised environment, there is the risk of contamination which means inspection data is much more

175 limited.

176   Table 1 lists several of the current protocols used to classify sewer pipe condition into various categories and

177   states, depending on the degree of complexity and context to account for. The different condition classes

178   should not be taken as an objective measure associated with functionality, as they are usually based on defects

179   identified on CCTV images with no causal link to measurable physical characteristics. CCTV inspection practices

180   persist to-date as the most requested method for condition and operational evaluation of sewer systems.

181   Despite the quality of CCTV footage obtained having markedly increased over the past decade, the CCTV

182   approach for sewer inspection continues to be criticised due to subjectively identifying individual defects

183   which do not map directly on asset performance (Dirksen et al. 2013; Van Riel et al. 2014; van Riel et al. 2016;

184   Li et al. 2019).

185   Currently, there is no single generalised framework to estimate pipe condition that can be used in both water

186   supply and wastewater collection and drainage systems, accounting for an "ideal" data set for deterioration

187   modelling at a network and to indicate emerging new inspection technologies that should be capable of

188   meeting the enhanced data needs. Although historically the management of water supply and sewerage/

189   drainage networks are generally considered separately, the authors believe that both types of pipe networks

190   have sufficient physical similarities, i.e. systems of buried jointed pipes so that condition assessment protocols

191   could be developed and applicable to both types of network. In both systems there are pressurized pipes that

192   are buried and subjected to time varying loading so that such pipes undergo similar mechanical processes, it

193   is accepted that corrosion processes are different but the mechanical consequences are similar. Clearly, sewer

194   and drainage systems are generally gravity driven, but their loading patterns could be seen as a subset of

195   pressurized pipes". There are more mature frameworks used in wastewater collection and drainage networks,

196   based on the identification of infrequent defects mainly by the use of CCTV. In water supply networks,

197   frameworks are emerging but their adoption is more challenging as there is no single dominant inspection

198   technology in use in water supply networks, and due to the more restricted access and risks to water quality

199   of invasive methods. In both applications the condition classification schemes do not have a direct and clear

200   link to system performance and serviceability. The inspection technologies used are generally high cost and

201 disruptive so only spatially sparse and infrequently collected data is available meaning that data on the

202 temporal change in the condition of any asset is rare.

203 **3.0 Deterioration Modelling**
204
205 Buried water supply and wastewater collection network infrastructure asset management usually involves the

206 process of collection of defect data using a range of methods and then mapping the defect data onto

207 corresponding asset condition and occasionally linking this to an assessment of the current performance of

208 pipe networks. It is unusual to directly link asset condition assessments and predictions of service levels from

209 performance models. To be able to estimate future performance of buried pipe networks it is important to be

210 able to estimate the rate of deterioration of individual assets, how these change with time and ultimately

211 impact on system performance.

212 Deterioration models for predicting the condition and performance of buried water assets are classified as

213 deterministic, statistical, probabilistic, data-driven (artificial neural networks (ANN), Fuzzy Logic (FL)) and

214 heuristic (Boxall et al. 2007; Clair and Sinha 2012). A summary of the different deterioration modelling

215 approaches and their predictive focus and relative data needs can be found in Table 2.

216 Statistical models that use current and historical maintenance and failure records, are the most common

217 approach used to forecast the number and rate of pipe/asset failures (e.g. Kleiner and Rajani 2001; Boxall et

218 al. 2007; Lawless 2011; Osman and Bainbridge 2011; Scheidegger et al. 2015). Typically, only a handful of data

219 parameters are applied to establish failure rate relationships often based simply on the pipe parameters (Hahn

220 and Shapiro 1994). Pipe networks that have a suitably sizable and dependable historical database are good

221 candidates for statistical models; nevertheless, the usefulness of statistical models is constrained when taking

222 into account newer pipes or other instances with limited historical and/or time dependent data e.g. local

223 environment information such as traffic loading or repair/refurbishment interventions.

224 Physical probabilistic models involve the application of statistical analysis, particularly in cases where historical

225 failure or inspection data is incomplete or unobtainable (Creighton 2012). The effect that disparate

226 parameters have on pipe performance are what these models specifically analyse as opposed to appraising

227 existing pipe failure records (Rajani and Kleiner 2001). These models claim to have the ability to predict the

8

228   probability of failure for a network of assets based on an appraisal of individual assets. Typically, they are used

229   where the progression of pipe deterioration and the loading conditions contributing to failure are well

230   characterised.

231   Data-driven approaches such as Artificial Neural Networks (ANN) have been used to establish pipe

232   deterioration rates by using data on component factors that are assumed to have an effect on the

233   serviceability of the pipe. The advantages of using ANN approaches are their ability to readily deal with

234   nonlinearity as well as inconsistent, messy data, and they can be adaptive to changing circumstances through

235   learning or retraining capabilities for varying data sets (Haykin 2010). The reliability of pipe deterioration rate

236   predictions can be improved by careful selection and data filtering of each of the component input

237   parameters. Machine learning algorithms and corresponding weights can be used to prioritise inspection of

238   these parameters. A barrier to successful implementation of this approach is often the need for an increased

239   level of skill to develop data pre-processing and interpretation methods (Landau 2012). These methods can

240   be employed to develop a model for asset groups for a whole network or an individual asset but are very

241   dependent on the availability of the initial training set (e.g. Wang et al. 2009), hence cohort models dominate

242   due to the sparsity of pipe specific data to learn from.

243   The use of engineering judgment and professional experience are intrinsically integrated within Fuzzy Logic

244   models that have been used to predict the pipe deterioration process. Where data is scarce or unobtainable,

245   tacit knowledge by way of wide ranging professional experience, then observations and model criteria

246   necessitate expression in ambiguous or "fuzzy" terms is the context where this type of model is used

247   (Sivanandam et al. 2007). This approach does however require significantly less asset data and condition data,

248   than other Machine Learning or statistical approaches to be implemented.

249   Deterministic models often use failure data from laboratory tests and sample specimens to obtain information

250   required to quantify the associations between component factors that contribute to failures. The relevance of

251   a deterministic model is thus limited to a discrete environment and should not be employed across different

252   environmental settings (Giustolisi et al. 2009). Deterministic models are founded on constrained parameters.

253   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

280   random model for estimating the evolution of the condition distribution of the network, particularly in the

281   context of limited data availability. Caradot et al. (2018) additionally demonstrated that statistical models have

282   a clear advantage compared to machine learning models at the network level when inferring outside the

283   observation window of the underlying data. Table 2 also highlights the inspection data needs of the different

284   approaches. It is seen that statistically based and ANN based approaches require significant amounts of asset

285   data both in terms of spatial coverage and temporal resolution, as their outputs focus on a single aspect of

286   asset performance and asset type. Probabilistic and heuristic models require less data and the incorporation

287   of tacit data in FL based models require the least amount of training/calibration data in order to deliver

288   consistent predictions of asset deterioration. In an earlier study, Clair and Sinha (2012) highlighted that several

289   water utilities have developed their own deterioration predictive models based on locally available condition

290   data. However, these models generally lack rigour and reliability when compared to models identified in

291   published literature (Table 2). By contrast, many of the models identified in the literature are problematic for

292   water utilities to employ as a result of their demanding data needs.

293   **4.0 Mechanisms for Deterioration**
294
295   This section examines the physical mechanisms that have been shown to influence the deterioration of buried

296   water supply, sewerage and drainage assets as well as how this knowledge has been used to develop models

297   to estimate the rates of asset deterioration.

298   There are a wide range of factors that can result in the sudden or progressive damage of pipes. The degree to

299   which each factor has an impact is dependent upon the location where the pipe is installed, the corresponding

300   characteristics of that location, the physical characteristics of the pipe, the operational conditions under which

301   the pipe is exposed to, and installation practice/workmanship which are a big factor in PVC fails for pipes

302   installed in the 1970s and has most recently given fusion joints a bad reputation. The level of influence brought

303   about by each factor should be a consideration when developing a predictive deterioration model (Liu and

304   Kleiner 2013). The factors have been categorised as Dynamic, Static, and Operational which include

305   environmental and physical parameters for water supply systems (Kleiner and Rajani 2002). Additional factors

306   for wastewater collection and drainage systems have been added to Figure 1.

307 Dynamic factors change over time and are often related to the environment surrounding a pipe. Ismail and El-

308 Shamy (2009) stated that the dynamic factors that contribute to pipe deterioration rates comprise, but are

309 not limited to, corrosivity of soil, flow rate, operating pressure, age of pipe and cumulative number of pipeline

310 breaks. Static factors in contrast remain unchanged over time as regarding properties of the pipe and

311 installation practice, and comprise pipe diameter, pipe material, and type of surrounding soil (El Chanati et al.

312 2016). Other factors such as bedding material and joint type and design (detailed in Table 3) should also be

313 considered as joints are a major point/mechanism for pipe deterioration and are a very significant area where

314 more data is needed beyond the dearth that now exists in industry.

315 Operational factors include wastewater characteristics and associated chemical and bioprocesses, sediment

316 level and repair and maintenance policies (Ana and Bauwens, 2010). Operational factors that contribute

317 towards pipe deterioration in water supply networks are water quality, water velocity and hydraulic pressure

318 variations caused by demand patterns and pump operations. The influence of applied pressure on the failure

319 rate of buried water networks was investigated by Shirzad et al. (2014) and also discussed by Rajeev et al.

320 (2014). Stress in the pipe material is the result of water pressure forces (Kabir et al. 2015), which are a

321 derivative of hydraulic demand, inherent structural integrity which is linked to water quality related corrosion

322 (within the pipe material) and the pressures from the surrounding soil which all influence the failure rate in

323 buried water pipes.

324 Environmental factors that contribute towards deterioration in pipes include ground movements caused by

325 seismic activity, groundwater dynamics and infiltration, freezing and thawing of the soil in which pipes are

326 installed and other nearby engineering activities leading to stress relaxations in the ground (Ismail and El-

327 Shamy 2009). The presence of trees, infiltration and exfiltration, the type of backfill or surface soil and surface

328 loads come under this classification (Ana and Bauwens 2010). Likewise, traffic loads and its accompanying

329 volume needs to be considered as it is directly proportional to the external loading on pipes and their joints,

330 which in some instances are believed to cause cyclic fatigue failures leading to bursts particularly in small

331 diameter pipes (Aydogdu and Firat 2015). The interaction of cyclic loadings (hydraulic transients, daily

332 pressures, traffic and soil movement) have been shown theoretically to dramatically reduce asset lifetime

333 (Brevis et al. 2016). In addition to the described factors, water quality (alkalinity, electoral conductivity, pH,

334 sulphate attack, residual chlorine, pH, and water temperature) causes pipe corrosion and subsequent

335 deterioration in a water network (Jun et al. 2020). Hydrogen sulphide generation in wastewater can also cause

336 significant deterioration in sewer pipes (Nielsen et al. 2008).

337 Pipe material is an important factor as different materials have different mechanical properties and so

338 deteriorate or fail in different ways. Pipe material also factors heavily when considering the performance of

339 pipes, more precisely their corrosion resistance and load carrying capacity (Berardi et al., 2008). Historically,

340 the most widely deployed materials for buried water supply and wastewater collection networks are made of

341 concrete, cement, cast iron, polyvinyl and ductile iron. Thick walled pipes exhibit more strength and greater

342 resistance to breakage than thin walled pipes. Thin walled pipes are also more prone to failure as the wall

343 thickness reduces due to corrosion caused by chemical and biological processes, further highlighting the

344 importance of the physical characteristics of the original pipe. Aydogdu and Firat (2015) postulate that the

345 diameter, age and length of the pipe are important factors with respect to deterioration and failure of buried

346 water supply networks. Furthermore, the deterioration rate becomes more pronounced in older pipes chiefly

347 because of legacy challenges that include being exposed to external stresses for long periods of time. Coating

348 and lining are important factors regarding corrosion as coated and lined pipes are less affected by the negative

349 effects of corrosion that increase the deterioration rate (Kutyłowska and Hotloś 2014). Sub-standard

350 installation practices and manufacturing faults of pipes are contributory factors in the deterioration and failure

351 of all types of buried pipes. Premature damage to a pipeline can be attributed to poor installation practices

352 used and to a lesser extent manufacturing faults. The type of joints the pipe has are also an influencing factor

353 in terms of failure (Folkman 2018).

354 Table 3 summarises key references relating to operational, environmental and physical factors affecting

355 deterioration. Out of the three component groups, the physical factors have the highest number of references.

356 While this might suggest that these are the most important factors, Malek Mohammadi et al. (2020) noted

357 that studies are also influenced by data availability and cost to collect data. Thus data on physical attributes

358   is likely to be more easily and cheaply available, whereas collecting environmental information can be time

359   consuming and expensive.

360   **5.0 Data Requirements for Understanding Pipe Condition and Deterioration**

361
362   It has been shown that existing methods to understand the current and likely future condition and

363   performance of buried water supply and sewerage pipes are limited by the complexity of the networks, the

364   multiple processes affecting deterioration and the scarcity of data about buried pipe condition, both spatially

365   and temporally, as well as limited data on the external environmental factors. Currently, commonly applied

366   statistically based deterioration models can on the whole only predict the probability of failure, based on

367   cohort modelling and are used by utilities to understand their future whole system rehabilitation needs. This

368   approach does not allow utility owners to know which specific pipes are closest to failure, rather which pipe

369   groups, based on the available data, are at highest risk of failure. Many authors have detailed the "ideal" data

370   requirements needed to create a more effective asset management strategy (Rokstad and Ugarelli 2016;

371   Carvalho et al. 2018) or the 'ideal' data set (Ahmadi et al. 2014). Taking into account the various factors that

372   influence individual asset deterioration listed in Table 3, "ideal" datasets for water utilities would need to be

373   wide ranging and include system and environment characteristics. These are summarised in Figures 2 and 3.

374   These figures show the range of information on asset characteristics during operational life and their

375   surrounding environmental factors but such elements are often missing from utilities' asset databases for

376   various reasons (Makana et al. 2020). Additional difficulties occur when there are inconsistencies relating to

377   historical information such as design drawings and as built drawings (Furlong et al. 2016). There often is a

378   recency bias when such asset information is attainable, and inconsistently collected data dictated by changes

379   in industry reporting standard operating procedures over time or protocols not being followed by water

380   utilities. Despite stringent data requirements and various acquisition method(s), there remains a latent level

381   of error and bias. Other data matters that are noteworthy include misplaced and questionable data, missing

382   information regarding rehabilitation works and the absence of environmental data (Egger et al. 2013).

383   Furthermore, operators may fail to increase capacity for data storage, and only store the most recent

384   information as part of their data management strategies. This results in inconsistencies in historical data

385   regarding network development, condition, operation and maintenance. Many existing data sets are based on

386   data collected from management and operational processes as well as the asset characteristics (Figure 2).

387   Collecting extra environmental data (Figure 3) is often linked with managing different data owners and

388   traversing differing data quality standards, and needs to be considered when developing data collection plans.

389   Much data may also still require digitisation and storage in relational databases to be useful.

390   While the condition of an asset can be described from sufficient observations of the physical pipe, the

391   performance of an asset requires additional information. To describe the current performance of an asset,

392   there is a need to understand the required performance to achieve the level of serviceability required by a

393   regulator (e.g. the number of allowable flooding incidents), but also how the pipe condition is affecting

394   performance. For example, as a pipe wall degrades, its hydraulic roughness is likely to increase and cross-

395   sectional area may also decrease (Boxall et al. 2004), thus decreasing the maximum potential flow rate for a

396   given pressure head difference. However, the impact of such condition changes might not be significant,

397   especially in terms of meeting the required level of serviceability. In fact it is expected that the relationship

398   between pipe condition and performance (and achieving levels of serviceability) is highly non-linear. Figure 4

399   describes a number of conceptual deterioration models describing physical deterioration and the consequent

400   impact on system performance in relation to a required level of serviceability. Physical asset deterioration can

401   be considered to occur linearly (A) in which the physical integrity of an asset deteriorates consistently with

402   time, or an asset suffers an unexpected but sudden loss in physical condition (B) combined with a consistent

403   deterioration rate.

404   Under the physical deterioration scenario A+B the performance of the asset initially deteriorates slowly (initial

405   phase) and it is only when the pipe has suffered a particular level of deterioration that the performance rapidly

406   deteriorates (second phase). However the link between asset condition and performance is unknown so rate

407   of performance reduction is very uncertain, especially in the second phase (A, B). It is prior to this rapid

408   deterioration in system performance that it is necessary to intervene. Combined with this concept of asset

409   condition and system performance, is the need to meet acceptable levels of performance. Figure 4 clearly

410   indicates that the ability to estimate the time to when system performance becomes unacceptable (optimum

15

411 intervention point) is strongly related to the rate at which system performance is lost in phase 2. It is clear

412 that for lower levels of serviceability then there is a higher level of uncertainty in determining the optimum

413 time for intervention. This requires new knowledge to link system performance and physical condition, the

414 ability to identify sudden performance loss (C) is also required. These requirements mean that much more

415 frequent and higher spatial resolution of asset inspection data over long time periods, or more adaptive

416 inspection capabilities (in which inspection frequency is linked with the rate of system performance decline)

417 is needed.

418 Selective survival bias is also an important issue when considering the future development of deterioration

419 models. Most of the current models are projected to underestimate the actual condition of the network as a

420 result of the infrequent asset condition observations used to inform model calibration, selectively accounting

421 for only the pipes that 'survived' until the date of inspection. This leads to a bias as the calibration of models

422 is built on data regarding pipes that are present at the time of inspection, hence underestimating system state,

423 which leads to overestimating the service life of pipes. Egger et al. (2013) suggested that an integration of the

424 deterioration model with a probabilistic replacement model that characterises the probability that the pipe

425 was not replaced at the time of inspection i.e. that the pipe is still in service, would be able to address the

426 selective survival bias issue. More frequent and data sets with higher spatial resolutions would also address

427 this issue.

428 Currently, the acquisition of data is a costly and disruptive exercise, which explains why data used to develop

429 deterioration models are limited in breadth, depth and quality (Ana et al. 2010). Condition-based maintenance

430 is hampered by limitations in data quality and quantity (space and time), which also impedes the mainstream

431 use of predictive deterioration models; a gap which in-pipe autonomous inspection robots (Fuentes et al.

432 2017; Thienen et al. 2018; Caffoor 2019; Mounce et al. 2021; Parrott et al. 2020) might overcome. Such new

433 pervasive inspection technologies may also provide a means to adding missing data/metadata. Statistically

434 based models need the most asset data and new inspection technologies, such as in-pipe robotics present the

435 potential for a step change in the management of water supply and sewerage pipes by reducing inspection

436 costs per unit length and disruption, while employing new sensing technologies to better characterise defects

437 and so define condition. Technology could therefore allow networks to be comprehensively and repeatedly

438 surveyed, as well as collecting a broader range of objective data. The data obtained has the potential to

439 transform deterioration modelling and allow utilities to have a higher degree of certainty as to which sections

440 of pipe should be repaired or replaced to maintain performance, while keeping costs to an affordable level.

441 The potential volumes of data however create significant challenges for storage and analysis to allow such

442 assessments to take place. Such practical considerations regarding the management of sewer asset data

443 management are discussed by Tscheikner-Gratl et al. (2019) in some detail.

444 Our contention is that what is buried within, and above on the ground is to some degree controlled by the soil

445 properties, in the sense that if the soil properties change, or the ground moves, the adjacent and/or overlying

446 elements of the infrastructure respond accordingly (i.e. deform transiently under transient applied loading or

447 deform permanently). To create a buried water pipe infrastructure inspection system able to manage,

448 coherently, what we do to the buried infrastructure (add new elements to it, repair or renovate it, maintain

449 it, or leave it alone – whatever ensures that it delivers the required level of serviceability into the future) we

450 need to be informed by the ground conditions and how the ground might react to that new activity or

451 intervention. The same argument holds for transport infrastructure – e.g. roads, railway, canals, whether on

452 the surface, in cuttings, on embankments or in tunnels. There remain few examples of studies (e.g. Clarke et

453 al. 2017) into the water utility–ground–surface transport infrastructure interdependency as a complete

454 system in terms of their condition, hence their likely future performance and as such what the corresponding

455 data model and data requirements will be in the context of in-pipe inspection robots. This systems approach

456 sets the basis for the ability to go beyond water industry specific data and mix different data sets that will form

457 the new horizon of what data architecture systems are needed to correspond with the deployment of in-pipe

458 inspection robots. A good example in practice of this type of approach to development of data models that

459 attempt to encapsulate multiple data sets for buried water pipe infrastructure, is both the Dutch

460 Gegevenswoordenboek Stedelijk Water data model (RIONED 2017) and Swiss data model (VSA-DSS 2014).

461 Both these data models contain a database structure specification, for example capturing existing utilities

462 data, and additionally enable other useful data sets (e.g. environmental and dynamic organisational data).

463 Furthermore, the most important feature of the two models is the facilitation of inputs from databases of

464 operational and maintenance data, for instance, databases regarding condition inspection reports or customer

465 complaints.

466 The present section demonstrates that by understanding the factors that drive asset deterioration and

467 highlighting the need to consistently link asset physical condition and system performance over the life of an

468 asset, there is a very clear need to justify improving the frequency and resolution of asset data collection over

469 current approaches used. New autonomous robotic inspection technologies that are currently emerging offer

470 a pragmatic way forward to expand the asset condition and performance data sets that water utilities can

471 collect (Thienen et al. 2018), and Mounce et al. (2021) conduct a detailed survey of the current landscape of

472 emerging autonomous technologies in what is still a field in its infancy. Nevertheless, water utilities also need

473 to collect environmental data (including data on other neighbouring buried assets systems) and link this into

474 enhanced asset deterioration models.

475 **6.0 Conclusions**
476
477 The paper has shown that current condition assessment methods are underpinned by inspection technologies

478 that locate and characterise discrete in-pipe defects. Such defect assessment methodologies are more mature

479 in wastewater collection and drainage systems than water supply systems. Traditionally inspection

480 technologies have been dominated by image based CCTV systems, although in the last few years significant

481 improvement has occurred in commercially available inspection systems, resulting in a new range of both free

482 swimming and tethered inspection systems focussed on better defect identification often to aid leakage

483 detection, structural integrity and flow capacity assessment. Condition assessment approaches are still

484 developing in water supply networks, due to even more limited access points and concerns over water safety

485 with invasive techniques, however a range of defect inspection technologies are emerging. In both network

486 types, condition assessment is limited by the cost, feasibility and disruption of the available methods. There

487 are deterioration modelling approaches that attempt to utilise the available data, but they are all restricted

488 by data availability and resolution issues. Even with improved inspection technologies, mentioned above it is

489 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

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.

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

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

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

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

536 Aydogdu, M., and Firat, M. (2015). "Estimation of failure rate in water distribution network using fuzzy
537 clustering and LS-SVM methods." *Water resources management*, 29(5), 1575-1590.
538 Babovic, V., Drecourt, J.-P., Keijzer, M., and Hansen, P. F. (2002). "A data mining approach to modelling of
539 water supply assets." *Urban water*, 4(4), 401-414.

541 Bakry, I., Alzraiee, H., Kaddoura, K., El Masry, M., and Zayed, T. (2016). "Condition prediction for chemical
542 grouting rehabilitation of sewer networks." *Journal of Performance of Constructed Facilities*, 30(6),
543 04016042.

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

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

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

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

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

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

565 Caradot, N., Riechel, M., Fesneau, M., Hernandez, N., Torres, A., Sonnenberg, H., Eckert, E., Lengemann, N.,
566 Waschnewski, J., and Rouault, P. (2018). "Practical benchmarking of statistical and machine learning models
567 for predicting the condition of sewer pipes in Berlin, Germany." *Journal of Hydroinformatics*, 20(5), 1131-
568 1147.

570 Caradot, N., Sonnenberg, H., Kropp, I., Ringe, A., Denhez, S., Hartmann, A., and Rouault, P. (2017). "The
571 relevance of sewer deterioration modelling to support asset management strategies." *Urban Water Journal*,
572 14(10), 1007-1015.

573

574 Carvalho, G., Amado, C., Brito, R. S., Coelho, S. T., and Leitão, J. P. (2018). "Analysing the importance of
575 variables for sewer failure prediction." *Urban Water Journal*, 15(4), 338-345.
576
577 Christodoulou, S., Aslani, P., and Vanrenterghem, A. (2003). "A risk analysis framework for evaluating
578 structural degradation of water mains in urban settings, using neurofuzzy systems and statistical modeling
579 techniques." *Proc., World Water & Environmental Resources Congress 2003*, 1-9.
580
581 Chughtai, F., and Zayed, T. (2008). "Infrastructure condition prediction models for sustainable sewer
582 pipelines." *Journal of Performance of Constructed Facilities*, 22(5), 333-341.
583
584 Chughtai, F., and Zayed, T. (2011). "Integrating WRc and CERIU condition assessment models and
585 classification protocols for sewer pipelines." *Journal of Infrastructure Systems*, 17(3), 129-136.
586
587 Clair, A. M., and Sinha, S. (2012). "State-of-the-technology review on water pipe condition, deterioration and
588 failure rate prediction models!" *Urban Water Journal*, 9(2), 85-112.
589
590 Clarke, B., Magee, D., Dimitrova, V., Cohn, A., Du, H., Mahesar, Q., Sadeghioon, A., Rogers, C., Gunn, D.,
591 Enwisle, D., Reeves, H., Stirling, R., and Glendinning, S. "A decision support system to proactively manage
592 subsurface utilities." *Proc., Proc of International Symposium for Next Generation Infrastructure (ISNGI), 11-*
593 *13 Sep 2017*, 99-108.
594
595 Creighton, J. H. (2012). *A first course in probability models and statistical inference*, Springer Science &
596 Business Media.
597
598 Cremer, F., van Deel, H.-G., Lehne, J., and Scholz, K. (2002). "Arbeitschilfen Abwasser Planung, Bau und
599 Betrieb von abwassertechnischen Anlagen in Liegenschaften des Bundes." *KA WASSERWIRTSCHAFT*
600 *ABWASSER*, 49(8), 1070-1077.
601
602 Davies, J., Clarke, B., Whiter, J., and Cunningham, R. (2001). "Factors influencing the structural deterioration
603 and collapse of rigid sewer pipes." *Urban water*, 3(1-2), 73-89.
604
605 Davis, Paul; Burn, S.; Gould, S.; Cardy, M.; Tjandraatmadja, G. F.; Sadler, Paul A. (2007a) Long term
606 performance prediction for PE pipes. [Project# 2975]. Denver, Colo.: AWWRF.
607 http://hdl.handle.net/102.100.100/125548?index=1
608
609 Davis, P., Burn, S., Moglia, M., and Gould, S. (2007b). "A physical probabilistic model to predict failure rates
610 in buried PVC pipelines." *Reliability Engineering System Safety*, 92(9), 1258-1266.
611
612 Davis, P., and Marlow, D. (2008). "Quantifying economic lifetime for asset management of large diameter
613 pipelines." *American Water Works Association*, 100(7), 110-119.
614
615 Davis, P., Silva, D. D., Marlow, D., Moglia, M., Gould, S., and Burn, S. (2008). "Failure prediction and optimal
616 scheduling of replacements in asbestos cement water pipes." *Journal of Water Supply: Research*
617 *Technology—AQUA*, 57(4), 239-252.
618
619 De Silva, D., Moglia, M., Davis, P., and Burn, S. (2006). "Condition Assessment and Probabilistic Analysis to
620 Estimate Failure Rates in Buried Pipelines." *Journal of Water Supply: Research and Technology-Aqua*, 55(3),
621 179-191.
622
623 Deb, A. K. (2002). *Prioritizing water main replacement and rehabilitation*, American Water Works
624 Association.

625   Dehghan, A., McManus, K., and Gad, E. (2008a). "Statistical analysis of structural failures of water pipes."
626   *Proc., Proceedings of the Institution of Civil Engineers-Water Management*, Thomas Telford Ltd, 207-214.
627

628   Dehghan, A., McManus, K. J., and Gad, E. F. (2008b). "Probabilistic failure prediction for deteriorating
629   pipelines: Nonparametric approach." *Journal of performance of constructed facilities*, 22(1), 45-53.
630

631   Dirksen, J., Clemens, F., Korving, H., Cherqui, F., Le Gauffre, P., Ertl, T., Plihal, H., Müller, K., and Snaterse, C.
632   (2013). "The consistency of visual sewer inspection data." *Structure and Infrastructure Engineering*, 9(3),
633   214-228.
634

635   Duchesne, S., Beardsell, G., Villeneuve, J. P., Toumbou, B., and Bouchard, K. (2013). "A survival analysis
636   model for sewer pipe structural deterioration." *Computer-Aided Civil and Infrastructure Engineering*, 28(2),
637   146-160.
638

639   DWA. (2016). Zustandserfassung und -beurteilung von Entwässerungssystemen außerhalb von Gebäuden -
640   Teil 7: Beurteilung der Umweltrelevanz des baulichen/betrieblichen Zustands [Condition assessment and
641   classification of urban drainage systems outside of buildings]. Hennef, Germany: Deutsche Vereinigung für
642   Wasserwirtschaft, Abwasser und Abfall e. V.
643

644   DWA. (2012). Leitfaden zur strategischen Sanierungsplanung von Entwässerungssystemen außerhalb von
645   Gebäuden [Guideline on strategical rehabilitation planning of urban drainage systems outside of buildings].
646   Hennef, Germany: Deutsche Vereinigung für Wasserwirtschaft, Abwasser und Abfall e. V.
647

648   Egger, C., Scheidegger, A., Reichert, P., and Maurer, M. (2013). "Sewer deterioration modeling with condition
649   data lacking historical records." *Water research*, 47(17), 6762-6779.
650

651   El Chanati, H., El-Abbasy, M. S., Mosleh, F., Senouci, A., Abouhamad, M., Gkountis, I., Zayed, T., and Al-
652   Derham, H. (2016). "Multi-criteria decision making models for water pipelines." *Journal of Performance of*
653   *Constructed Facilities*, 30(4), 04015090.
654

655   EN 752. (2008). Drain and sewer systems outside of buildings. CEN, Brussels.
656

657   EN 13508-2. (2011). Investigation and Assessment of Drain and Sewer Systems Outside Buildings–Part 2:
658   Visual Inspection Coding System.
659

660   Fares, H., and Zayed, T. (2010). "Hierarchical fuzzy expert system for risk of failure of water mains." *Journal*
661   *of Pipeline Systems Engineering Practice*, 1(1), 53-62.
662

663   Farshad, M. (2004). "Two new criteria for the service life prediction of plastics pipes." *Polymer Testing*, 23(8),
664   967-972.
665

666   Folkman, S. (2018). "Water main break rates in the USA and Canada: A comprehensive study." *Utah State*
667   *University*, Buried Structures Laboratory.
668

669   Fox, S., Shepherd, W., Collins, R., and Boxall, J. (2016). "Experimental quantification of contaminant ingress
670   into a buried leaking pipe during transient events." *Journal of Hydraulic Engineering*, 142(1), 04015036.
671

672   Fuentes, R., Chapman, T., Cook, M., Scanlan, J., Li, Z., and Richardson, R. C. (2017). "Briefing: UK-RAS white
673   paper in robotics and autonomous systems for resilient infrastructure." *Proceedings of the Institution of Civil*
674   *Engineers-Smart Infrastructure and Construction*, 170(3), 72-79.
675

676 Gedam, A., Mangulkar, S., and Gandhi, B. (2016). "Prediction of sewer pipe main condition using the linear
677 regression approach." *Journal of Geoscience and Environment Protection*, 4(5), 100-105.
678
679 Geem, Z. W., Tseng, C.-L., Kim, J., and Bae, C. (2007). "Trenchless water pipe condition assessment using
680 artificial neural network." *Pipelines 2007: Advances and Experiences with Trenchless Pipeline Projects*, 1-9.
681
682 Giustolisi, O., Laucelli, D., and Colombo, A. F. (2009). "Deterministic versus stochastic design of water
683 distribution networks." *Journal of Water Resources Planning Management*, 135(2), 117-127.
684
685 Hahn, G. J., and Shapiro, S. S. (1994). *Statistical models in engineering*, Wiley, New York.
686
687 Harvey, R. R., and McBean, E. A. (2014). "Comparing the utility of decision trees and support vector machines
688 when planning inspections of linear sewer infrastructure." *Journal of Hydroinformatics*, 16(6), 1265-1279.
689
690 Haykin, S. (2010). *Neural Networks and Learning Machines, 3/E*, Pearson Education India.
691
692 Hernández, N., Caradot, N., Sonnenberg, H., Rouault, P., and Torres, A. (2018). "Support tools to predict the
693 critical structural condition of uninspected pipes for case studies of Germany and Colombia." *Water Practice
694 & Technology*, 13(4), 794-802.
695
696 Hukka, J. J., and Katko, T. S. (2015). "Resilient asset management and governance for deteriorating water
697 services infrastructure." *Procedia Economics and Finance*, 21, 112-119.
698
699 IKT. (2014). Bildreferenzkatalog - Private Abwasserleitungen (In German, Image Reference Catalog - Private
700 Sewers), available at: https://www.ikt.de/blog/neuer-bildreferenzkatalog-zu-schaeden-an-privaten-
701 abwasserleitungen/ (Accessed: 22 September 2021).
702
703 Ismail, A., and El-Shamy, A. (2009). "Engineering behaviour of soil materials on the corrosion of mild steel."
704 *Applied clay science*, 42(3-4), 356-362.
705
706 Jones, D. F., Mirrazavi, S. K., and Tamiz, M. (2002). "Multi-objective meta-heuristics: An overview of the
707 current state-of-the-art." *European journal of operational research*, 137(1), 1-9.
708
709 Jun, H. J., Park, J. K., and Bae, C. H. (2020). "Factors affecting steel water-transmission pipe failure and pipe-
710 failure mechanisms." *Journal of Environmental Engineering*, 146(6), 04020034.
711
712 Kabir, G., Tesfamariam, S., Francisque, A., and Sadiq, R. (2015). "Evaluating risk of water mains failure using a
713 Bayesian belief network model." *European Journal of Operational Research*, 240(1), 220-234.
714
715 Kabir, G., Balek, N. B. C., and Tesfamariam, S. (2018). "Sewer structural condition prediction integrating
716 Bayesian model averaging with logistic regression." *Journal of Performance of Constructed Facilities*, 32(3),
717 04018019.
718
719 Kakoudakis, K., Behzadian, K., Farmani, R., and Butler, D. (2017). "Pipeline failure prediction in water
720 distribution networks using evolutionary polynomial regression combined with K-means clustering." *Urban
721 Water Journal*, 14(7), 737-742.
722
723 Khan, Z., Zayed, T., and Moselhi, O. (2010). "Structural condition assessment of sewer pipelines." *Journal of
724 performance of constructed facilities*, 24(2), 170-179.
725

726 Khazraeializadeh, S., Gay, L. F., and Bayat, A. (2014). "Comparative analysis of sewer physical condition
727 grading protocols for the City of Edmonton." *Canadian Journal of Civil Engineering*, 41(9), 811-818.
728
729 Kim, J., Bae, C., Woo, H., Kim, J., and Hong, S. (2007). "Assessment of residual tensile strength on cast iron
730 pipes." *Pipelines 2007: Advances and Experiences with Trenchless Pipeline Projects*, 1-7.
731
732 Kleiner, Y., Nafi, A., and Rajani, B. (2010). "Planning renewal of water mains while considering deterioration,
733 economies of scale and adjacent infrastructure." *Water Science Technology: Water Supply*, 10(6), 897-906.
734
735 Kleiner, Y., and Rajani, B. (1999). "Using limited data to assess future needs." *Journal-American Water Works*
736 *Association*, 91(7), 47-61.
737
738 Kleiner, Y., and Rajani, B. (2001). "Comprehensive review of structural deterioration of water mains:
739 statistical models." *Urban water*, 3(3), 131-150.
740
741 Kleiner, Y., and Rajani, B. (2002). "Forecasting variations and trends in water-main breaks." *Journal of*
742 *infrastructure systems*, 8(4), 122-131.
743
744 Kleiner, Y., and Rajani, B. (2008). "Prioritising individual water mains for renewal." *Proc., World*
745 *Environmental and Water Resources Congress 2008: Ahupua'A*, 1-10.
746
747 Kleiner, Y., Rajani, B., and Sadiq, R. (2005). *Risk management of large-diameter water transmission mains*,
748 AWWA Research Foundation and American Water Works Association.
749
750 Kleiner, Y., Sadiq, R., and Rajani, B. (2004). "Modeling failure risk in buried pipes using fuzzy Markov
751 deterioration process." *Pipeline Engineering and Construction: What's on the Horizon?*, 1-12.
752
753 Kley, G., Kropp, I., Schmidt, T., and Caradot, N. (2013). "SEMA D1. 1-Review of Available Technologies and
754 Methodologies for Sewer Condition Evaluation." Berlin, Germany: Kompetenzzentrum Wasser Berlin.
755
756 Koo, D.-H., and Ariaratnam, S. T. (2006). "Innovative method for assessment of underground sewer pipe
757 condition." *Automation in construction*, 15(4), 479-488.
758
759 Kutyłowska, M., and Hotloś, H. (2014). "Failure analysis of water supply system in the Polish city of Głogów."
760 *Engineering Failure Analysis*, 41, 23-29.
761
762 Laakso, T., Kokkonen, T., Mellin, I., and Vahala, R. (2018). "Sewer condition prediction and analysis of
763 explanatory factors." *Water*, 10(9), 1239.
764
765 Landau, L. J. (2012). *Concepts for neural networks: A survey*, Springer Science & Business Media.
766
767 Lawless, J. F. (2011). *Statistical models and methods for lifetime data*, John Wiley & Sons.
768
769 Le Gat, Y., and Eisenbeis, P. (2000). "Using maintenance records to forecast failures in water networks."
770 *Urban water*, 2(3), 173-181.
771
772 Le Gat, Y. (2008). "Modelling the deterioration process of drainage pipelines." *Urban Water Journal*, 5(2), 97-
773 106.
774

775 Le Gauffre, P., Joannis, C., Vasconcelos, E., Breysse, D., Gibello, C., and Desmulliez, J.-J. (2007). "Performance
776 indicators and multicriteria decision support for sewer asset management." *Journal of Infrastructure*
777 *Systems*, 13(2), 105-114.
778
779 Li, D., Cong, A., and Guo, S. (2019). "Sewer damage detection from imbalanced CCTV inspection data using
780 deep convolutional neural networks with hierarchical classification." *Automation in Construction*, 101, 199-
781 208.
782
783 Li, Z., Zhang, B., Wang, Y., Chen, F., Taib, R., Whiffin, V., and Wang, Y. (2014). "Water pipe condition
784 assessment: a hierarchical beta process approach for sparse incident data." *Machine learning*, 95(1), 11-26.
785
786 Liu, Z., and Kleiner, Y. (2013). "State of the art review of inspection technologies for condition assessment of
787 water pipes." *Measurement*, 46(1), 1-15.
788
789 Loganathan, G. V., Park, S., and Sherali, H. (2002). "Threshold break rate for pipeline replacement in water
790 distribution systems." *Journal of water resources planning management*, 128(4), 271-279.
791
792 Lu, J. P., Davis, P., and Burn, L. (2003). "Lifetime prediction for ABS pipes subjected to combined pressure
793 and deflection loading." *Polymer Engineering Science*, 43(2), 444-462.
794
795 Lubini, A. T., and Fuamba, M. (2011). "Modeling of the deterioration timeline of sewer systems." *Canadian*
796 *Journal of Civil Engineering*, 38(12), 1381-1390.
797
798 Makar, J. (1999). "Diagnostic techniques for sewer systems." *Journal of Infrastructure Systems*, 5(2), 69-78.
799
800 Makropoulos, C., and Butler, D. (2005). "A neurofuzzy spatial decision support system for pipe replacement
801 prioritisation." *Urban Water Journal*, 2(3), 141-150.
802
803 Mashford, J., Marlow, D., Tran, D., and May, R. (2011). "Prediction of sewer condition grade using support
804 vector machines." *Journal of Computing in Civil Engineering*, 25(4), 283-290.
805
806 Malek Mohammadi, M., Najafi, M., Kermanshachi, S., Kaushal, V., and Serajiantehrani, R. (2020). "Factors
807 Influencing the Condition of Sewer Pipes: State-of-the-Art Review." *Journal of Pipeline Systems Engineering*
808 *and Practice*, 11(4), 03120002.
809
810 Marlow, D., Davis, P., Beale, D., Burn, S., and Urquhart, A. (2009). *Remaining asset life: A state of the art*
811 *review*, Water Environment Research Foundation.
812
813 McDonald, S., Zhao, J., and Yehuda, K. (2001). "Guidelines for condition assessment and rehabilitation of
814 large sewers." *Institute for Research in Construction National Research Council Canada, K1A0R6*.
815
816 Micevski, T., Kuczera, G., and Coombes, P. (2002). "Markov model for storm water pipe deterioration."
817 *Journal of infrastructure systems*, 8(2), 49-56.
818
819 Moglia, M., Davis, P., and Burn, S. (2008). "Strong exploration of a cast iron pipe failure model." *Reliability*
820 *Engineering System Safety*, 93(6), 885-896.
821
822 Mohammadi, M. M., Najafi, M., Tabesh, A., Riley, J., and Gruber, J. (2019). "Condition prediction of sanitary
823 sewer pipes." *Pipelines 2019: Condition Assessment, Construction, and Rehabilitation*, American Society of
824 Civil Engineers Reston, VA, 117-126.
825

826 Mounce, S. R., Shepherd, W. J., Boxall, J. B., Horoshenkov, K. V., and Boyle, J. H. (2021). "Autonomous
827 robotics for water and sewer networks." *IAHR Hydrolink*, 2.
828
829 Najafi, M., and Kulandaivel, G. (2005). "Pipeline condition prediction using neural network models." *Pipelines*
830 *2005: Optimizing Pipeline Design, Operations, and Maintenance in Today's Economy*, 767-781.
831
832 Najjaran, H., Rajani, B., and Sadiq, R. (2004). "A fuzzy expert system for deterioration modeling of buried
833 metallic pipes." *Proc., IEEE Annual Meeting of the Fuzzy Information, 2004. Processing NAFIPS'04.*, IEEE, 373-
834 378.
835
836 Najjaran, H., Sadiq, R., and Rajani, B. (2006). "Fuzzy expert system to assess corrosion of cast/ductile iron
837 pipes from backfill properties." *Computer-Aided Civil Infrastructure Engineering*, 21(1), 67-77.
838
839 NASSCO (2016). Pipeline Assessment Certification Program (PACP), Frederick, MD, USA: National Association
840 of Sewer Service Companies.
841
842 National Archives (2008). The Water Supply and Sewerage Services (Customer Service Standards)
843 Regulations, https://www.legislation.gov.uk/uksi/2008/594/schedules, accessed 28/09/21.
844
845 National Research Council Canada (2003). "Deterioration and inspection of water distribution systems, a best
846 practice by the national guide to sustainable municipal infrastructure." *Federation of Canadian*
847 *Municipalities and National Research Council* (1.1).
848
849 Nielsen, A. H., Vollertsen, J., Jensen, H. S., Wium-Andersen, T., and Hvitved-Jacobsen, T. (2008). "Influence of
850 pipe material and surfaces on sulfide related odor and corrosion in sewers." *Water Research*, 42(15), 4206-
851 4214.
852
853 Oliveira, D., Guo, W., Soibelman, L., and Garrett, J., James H (2007). "Spatial Data Management and Analysis
854 in Sewer Systems' Condition Assessment: an Overview." *Computing in Civil Engineering (2007)*, 391-398.
855
856 Ormsby, C. (2009). "A framework for estimating the total cost of buried municipal infrastructure renewal
857 projects." MS Thesis, Department of Civil Engineering and Applied Mechanics, McGill University, Montreal,
858 CN.
859
860 Osman, H., and Bainbridge, K. (2011). "Comparison of statistical deterioration models for water distribution
861 networks." *Journal of Performance of Constructed Facilities*, 25(3), 259-266.
862
863 Park, S. W., and Loganathan, G. (2002). "Methodology for economically optimal replacement of pipes in
864 water distribution systems: 1. Theory." *KSCE Journal of Civil engineering*, 6(4), 539-543.
865
866 Parrott, C., Dodd, T. J., Boxall, J., and Horoshenkov, K. (2020). "Simulation of the behavior of biologically-
867 inspired swarm robots for the autonomous inspection of buried pipes." *Tunnelling and Underground Space*
868 *Technology*, 101, 103356.
869
870 Pelletier, G., Mailhot, A., and Villeneuve, J.-P. (2003). "Modeling water pipe breaks—Three case studies."
871 *Journal of water resources planning management*, 129(2), 115-123.
872
873 Poulton, M., Le Gat, Y., and Brémond, B. (2009). "The impact of pipe segment length on break predictions in
874 water distribution systems." *Strategic Asset Management of Water Supply Wastewater Infrastructures*, 419.
875

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

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

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

885 Rajani, B., and Tesfamariam, S. (2007). "Estimating time to failure of cast-iron water mains." *Proceedings of*
886 *the Institution of Civil Engineers-Water Management*, 160(2), 83-88.
887 Rajeev, P., Kodikara, J., Robert, D., Zeman, P., and Rajani, B. (2014). "Factors contributing to large diameter
888 water pipe failure." *Water asset management international*, 10(3), 9-14.

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

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

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

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

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

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

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

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

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

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

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

924

925 Shirzad, A., Tabesh, M., and Farmani, R. (2014). "A comparison between performance of support vector
926 regression and artificial neural network in prediction of pipe burst rate in water distribution networks." *KSCE*
927 *Journal of Civil Engineering*, 18(4), 941-948.
928
929 Sivanandam, S., Sumathi, S., and Deepa, S. (2007). *Introduction to fuzzy logic using MATLAB*, Springer.
930 Sousa, V., Matos, J. P., and Matias, N. (2014). "Evaluation of artificial intelligence tool performance and
931 uncertainty for predicting sewer structural condition." *Automation in Construction*, 44, 84-91.
932
933 Tesfamariam, S., Rajani, B., and Sadiq, R. (2006). "Possibilistic approach for consideration of uncertainties to
934 estimate structural capacity of ageing cast iron water mains." *Canadian Journal of Civil Engineering*, 33(8),
935 1050-1064.
936
937 Thienen, P., Bergmans, B., and Diemel, R. (2018). "Advances in Development and Testing of a System of
938 Autonomous Inspection Robots for Drinking Water Distribution Systems." *Proc., WDSA/CCWI Joint*
939 *Conference Proceedings*.
940
941 Tran, D., Ng, A., Perera, B. J. C., Burn, S., and Davis, P. (2006). "Application of probabilistic neural networks in
942 modelling structural deterioration of stormwater pipes." *Urban Water Journal*, 3(3), 175-184.
943
944 Tran, D., Perera, B. C., and Ng, A. (2009). "Comparison of structural deterioration models for stormwater
945 drainage pipes." *Computer-Aided Civil and Infrastructure Engineering*, 24(2), 145-156.
946
947 Tran, D. H., Ng, A., and Perera, B. J. C. (2007). "Neural networks deterioration models for serviceability
948 condition of buried stormwater pipes." *Engineering Applications of Artificial Intelligence*, 20(8), 1144-1151.
949
950 Tscheikner-Gratl, F., Caradot, N., Cherqui, F., Leitão, J. P., Ahmadi, M., Langeveld, J. G., Le Gat, Y., Scholten,
951 L., Roghani, B., and Rodríguez, J. P. (2019). "Sewer asset management–state of the art and research needs."
952 *Urban Water Journal*, 16(9), 662-675.
953
954 USEPA (2002). "Deteriorating Buried Infrastructure Management Challenges and Strategies." U. S. E. P. A.
955 (USEPA), ed., American Water Works Service Co. Inc., Engineering Department, Washington DC.
956
957 van Riel, W., Langeveld, J., Herder, P., and Clemens, F. (2014). "Intuition and information in decision-making
958 for sewer asset management." *Urban Water Journal*, 11(6), 506-518.
959
960 van Riel, W., van Bueren, E., Langeveld, J., Herder, P., and Clemens, F. (2016). "Decision-making for sewer
961 asset management: Theory and practice." *Urban Water Journal*, 13(1), 57-68.
962
963 Vanrenterghem-Raven, A. (2007). "Risk factors of structural degradation of an urban water distribution
964 system." *Journal of infrastructure systems*, 13(1), 55-64.
965
966 VSA-DSS (2014). "Datenstruktur Siedlungsentwässerung [Data Structure Urban Water]."
967
968 Wang, C.-w., Niu, Z.-g., Jia, H., and Zhang, H.-w. (2010). "An assessment model of water pipe condition using
969 Bayesian inference." *Journal of Zhejiang University-SCIENCE A*, 11(7), 495-504.
970
971 Wang, Y., Zayed, T., and Moselhi, O. (2009). "Prediction models for annual break rates of water mains."
972 *Journal of performance of constructed facilities*, 23(1), 47-54.
973
974 Wasson, C. S. (2015). *System engineering analysis, design, and development: Concepts, principles, and*
975 *practices*, John Wiley & Sons.

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

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

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

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

987 WRc. (2021). Sewerage Risk Manual. Available at: http://srm.wrcplc.co.uk/home.aspx [Accessed
988 22/09/2021].

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

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

997 **List of Figure Captions**

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

1001 **Figure 2**: Optimal dataset required for key asset characteristics of water and wastewater networks

1003 **Figure 3**: Optimal environmental dataset for buried assets of water and wastewater networks

1005 **Figure 4**: Conceptual relationships between asset condition, system performance and times to attain
1006 unacceptable levels of performance

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1009   **<u>Tables</u>**

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1011   *Table 1: Current protocols that are used to evaluate the condition and performance of a sewer pipe, modified*
1012   *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

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014 *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).

015 **DR**: Data Requirements
016 **Key**: ↑ High, ↔ Medium, ↓ Low
017 **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

Factors that contribute to the deterioration of buried water infrastructure

Operational Factors
- Cathodic Protection
- Incorrect Operation
- Maintenance Practices
- Water Pressure
- Flow Velocity
- Chemical Processes
- Bio Processes
- Sediments/Solids
- Pump Operation

Dynamic Factors
- Environmental
  - Climate
  - Temperature
  - Ground Movement
  - Soil Moisture
  - Electrical Resistivity
  - Groundwater Level
- External Loads
  - Traffic Loads
  - Accidental Loads

Static Factors
- Pipe Material
- Pipe Diameter
- Wall Thickness
- Pipe Depth
- Trench Backfill
- Soil Type
- Installation Practice
- Joint Type
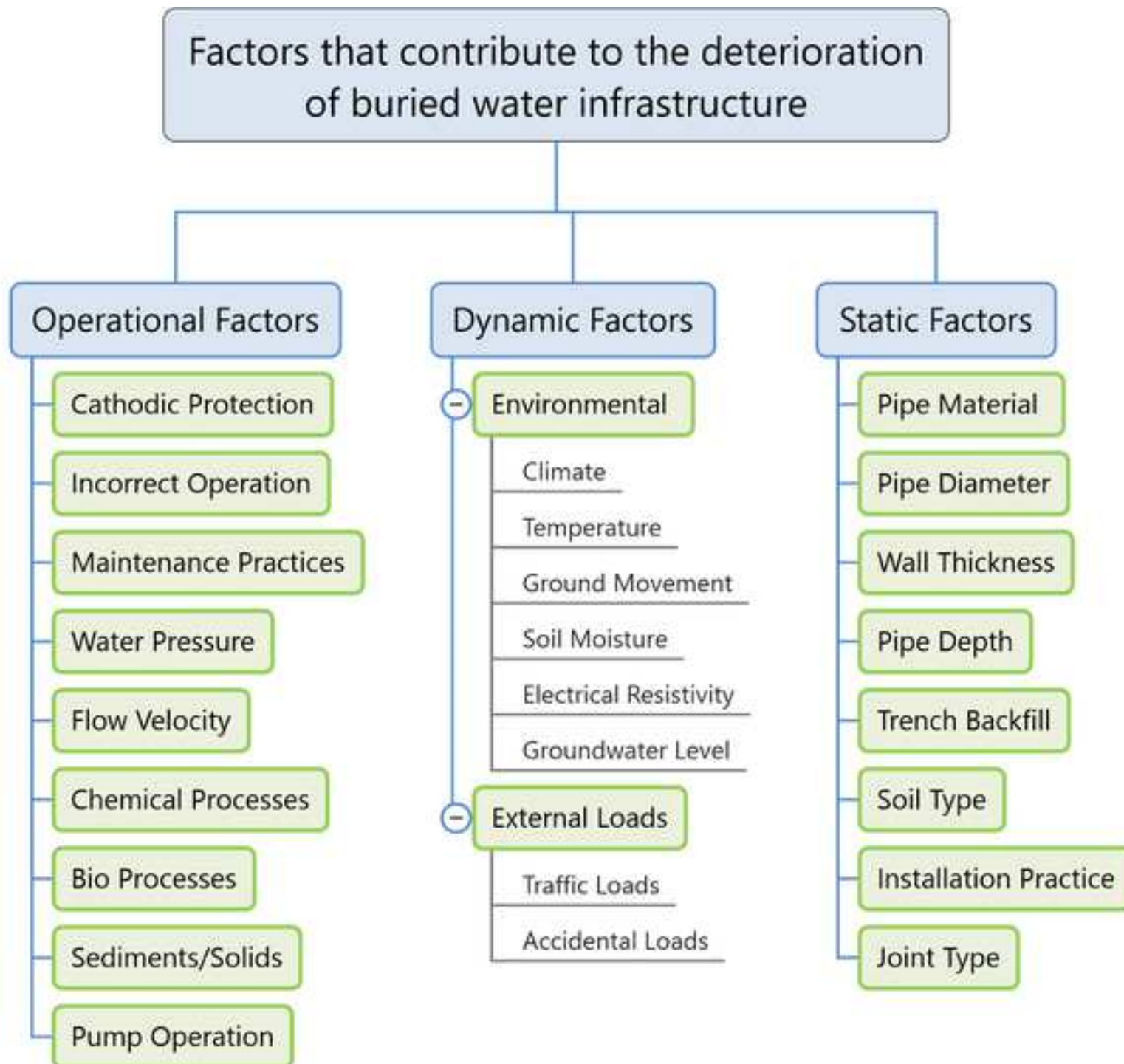
Figure 2 :Optimal dataset required for key asset characteristics of water and wastewater networks

Optimal Dataset Regarding Water and Wastewater Networks

Water distribution
- Dimension
- Pipe material
- Position (coordinates) of the pipes
- Pipe length
- Material of pipe bed
- Type of pipe connection
- Failure statistics
- Leakage
- Hydrodynamic network model
- Time interval between on-site inspections
- Year of construction
- Depth of cover
- Quality of water

Wastewater collection
- Dimension
- Pipe shape
- Pipe material
- Position (coordinates) of the pipes
- Pipe length
- Material of pipe bed
- Type of pipe connection
- Failure statistics
- Hydrodynamic network model
- Time interval between on-site inspections and the derived condition state
- Year of construction
- Depth of cover
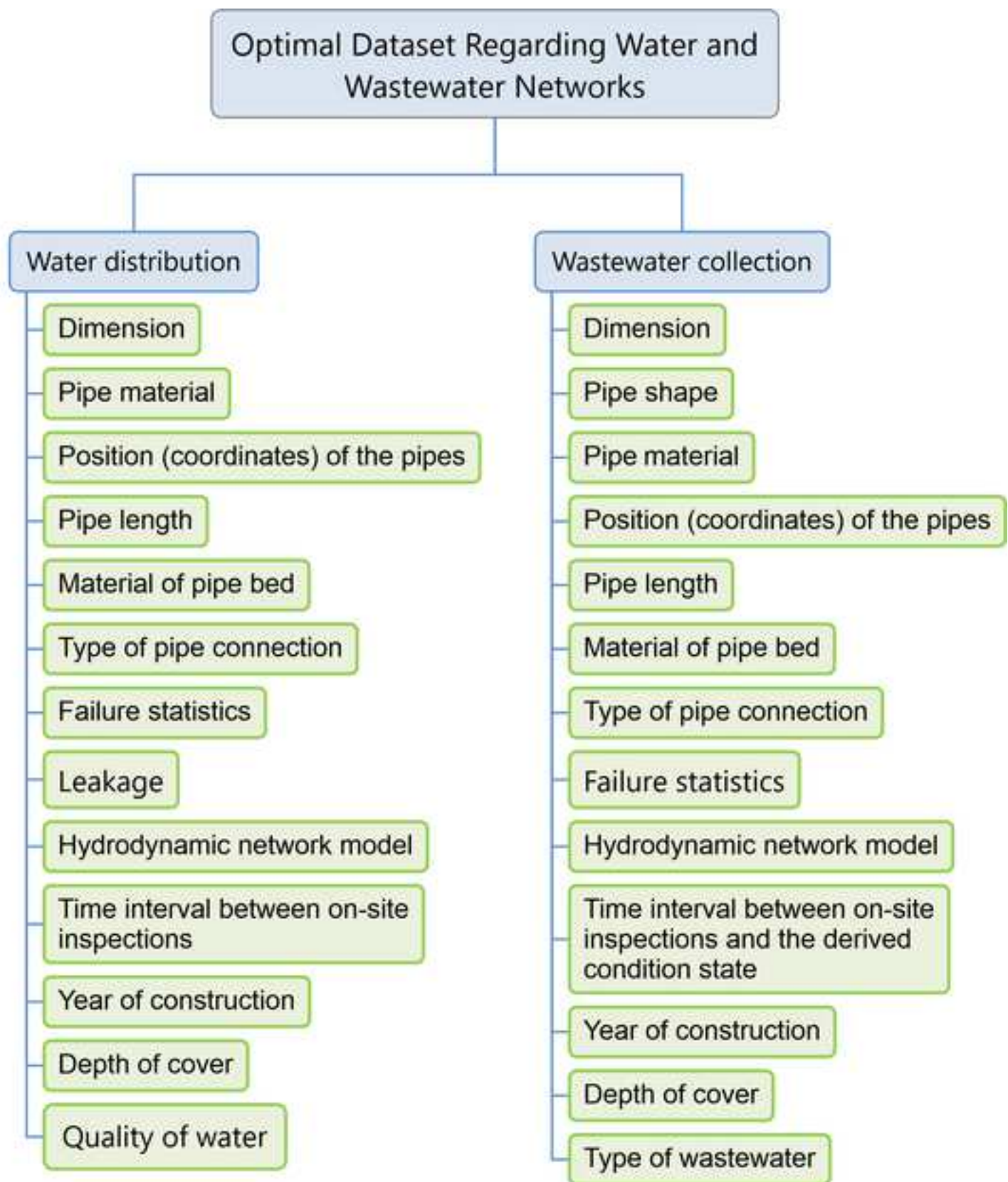- Type of wastewater

Figure 3: Optimal environmental dataset for buried assets of water and wastewater networks
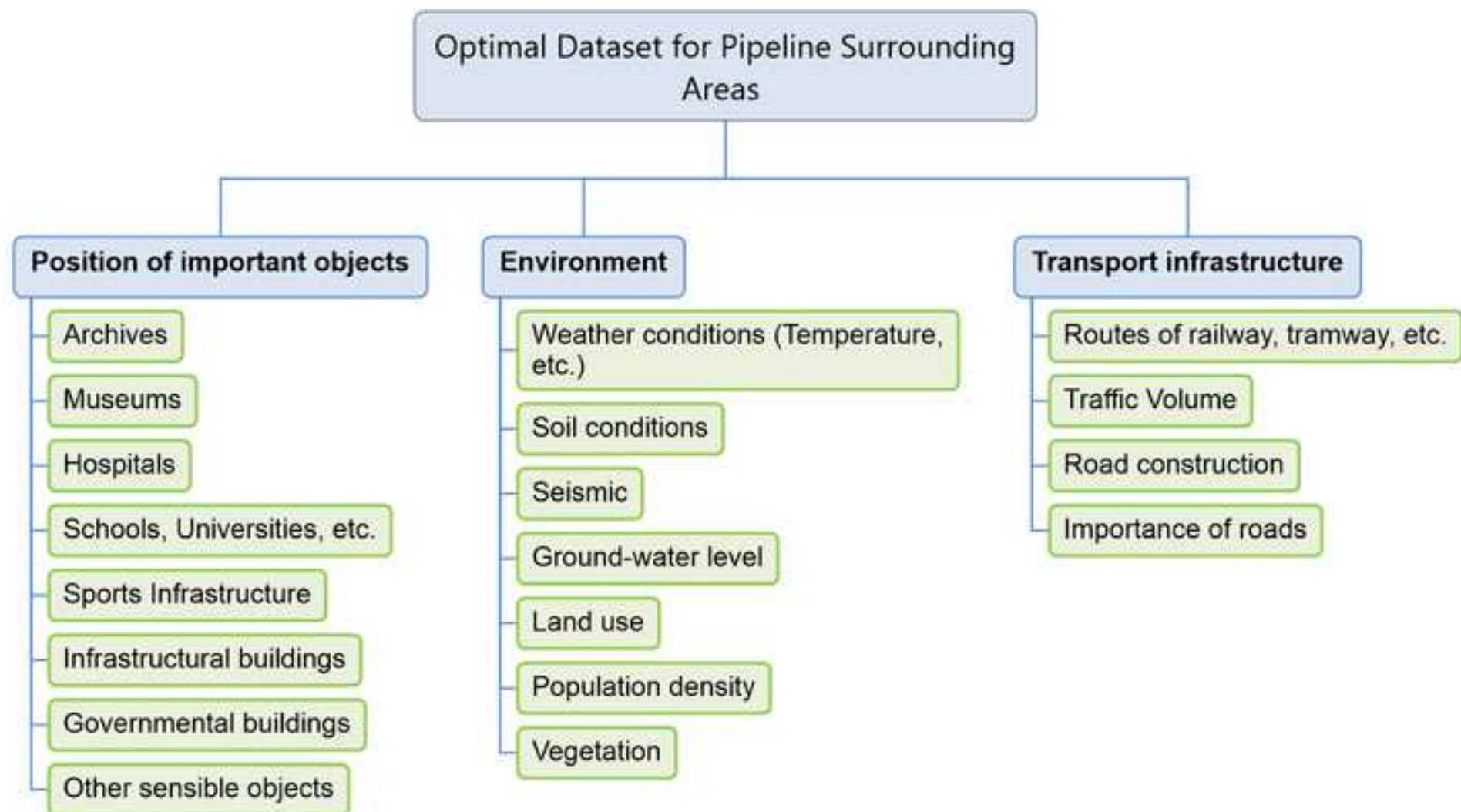
Figure 4: Conceptual relationships between asset condition, system performance and times to attain unacceptable levels of performance