

Future inspection and deterioration prediction capabilities for buried distributed water infrastructure

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

2

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41

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

43

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

44

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

45

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

46

46 assessment frameworks, mainly based on asset defect location, identification and characterisation. These are

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

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

55 56 **1.0 Introduction**

57
58 One of the fundamental needs of human settlements is a source of clean water – without this, people cannot
59 survive. To this basic need should be added the facility to remove wastewater and also deal with excessive
60 surface water arising from precipitation and overland and ground flows. Water supply pipes normally operate
61 under pressurized conditions, in which the internal pressure varies but is always higher than atmospheric
62 pressure, wastewater collection and storm water drainage systems generally operate in an unpressurized
63 state. In developed countries, the systems have been in operation for a very long time, have been constructed
64 from a wide variety of materials, and have been progressively added to. The materials that make up these
65 buried pipe networks are naturally subjected to chemical, physical and biological stresses, and the pipe
66 networks typically therefore suffer from deterioration over time in a variety of ways. Those operating these
67 networks are responsible for maintaining adequate quality of service delivery, and therefore an understanding
68 of when the systems are likely to fail, or deteriorate to a point of adversely influencing the service provision,
69 is vital. Failure of both water supply, wastewater collection and drainage networks can be defined as an
70 inability to carry the required flows, whether that be wastewater flows, stormwater rainfall runoff flows, or
71 supplying potable water demand and maintaining the ability to pass even higher flows for firefighting
72 purposes. Pipes should also convey flows with acceptable levels of exfiltration/infiltration and leakage and for
73 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.

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

140 **2.0 Condition Assessment**

141
142 Once installed, the pipe structure and the inner wall surface of buried pipes can deteriorate (Kleiner and Rajani
143 2001). Structural deterioration results in buried pipes having a diminished capacity to resist physical stresses,
144 while deterioration of the inner surfaces of pipes results in a reduction of hydraulic capacity, degradation of
145 water quality, and the diminished capacity to resist internal corrosion. Both categories of deterioration can
146 lead to serviceability failures in pipe systems; the risk of such failure is estimated based on the condition of
147 individual pipes.

148 At present standardised condition assessment protocols exist and are in regular use in industrial piping, oil
149 and gas pipelines, and wastewater collection systems. A wide ranging field of research studies has been
150 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

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

254 available to estimate pipe deterioration rates. Empirical models are only applicable to assets that are similar,
255 while physical models are often applied to individual assets. Deterministic models that are empirical should
256 only be used on types of pipes that have suitable and dependable historical pipe failure data (Marlow et al.
257 2009).

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

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

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

277 A small number of studies have assessed the performance of deterioration models to simulate the condition
278 distribution of the network (Duchesne et al. 2013; Ugarelli et al. 2013; Caradot et al. 2017; Caradot et al. 2018;
279 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, electrical 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 Hotłoś 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

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

490 deterioration modelling approaches still identify the risk of failure in asset cohorts rather than at individual
491 assets, usually based on repair or maintenance data rather than inspection data. The paper has identified new
492 idealised optimal data needs for both network types as well as their surrounding areas, and their relationships
493 between asset condition, system performance and times to attain unacceptable levels of performance: wider
494 range of factors that should be monitored and better temporal and spatial resolution. If these new data needs
495 can be met then deterioration modelling approaches could be developed to identify individual assets with a
496 high risk of failing to meet required levels of serviceability and hence limited investment be best targeted. The
497 study also identified emerging robotic inspection technologies that are autonomous and capable of utilising a
498 wider range of sensors to collect the required asset data at a much higher spatial and temporal resolution,
499 and readily enable repeat inspection which is key to many deterioration modelling techniques. Such improved
500 asset data sets combined with environmental data from other datasets could enable the development of much
501 more reliable asset and system performance deterioration models, thus allowing for the first time focussed
502 proactive repair and rehabilitation of assets.

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505 **Data Availability Statement**

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

508 **8.0 References**

- 509
- 510 Achim, D., Ghotb, F., and McManus, K. (2007). "Prediction of water pipe asset life using neural networks."
511 *Journal of infrastructure systems*, 13(1), 26-30.
- 512
- 513 Ahmadi, M., Cherqui, F., De Massiac, J.-C., and Le Gauffre, P. (2014). "From sewer inspection programmes to
514 rehabilitation needs: research and results related to data quality and availability with the support of
515 numerical experiment." *European journal of environmental and civil engineering*, 18(10), 1145-1156.
- 516
- 517 Al-Barqawi, H., and Zayed, T. (2006). "Condition rating model for underground infrastructure sustainable
518 water mains." *Journal of Performance of Constructed Facilities*, 20(2), 126-135.
- 519
- 520 Al-Barqawi, H., and Zayed, T. (2008). "Infrastructure management: Integrated AHP/ANN model to evaluate
521 municipal water mains' performance." *Journal of Infrastructure Systems*, 14(4), 305-318.
- 522

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.
525

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.
529

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.
532

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.
535

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.
540

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.
544

545 Balekelayi, N., and Tesfamariam, S. (2019). "Statistical inference of sewer pipe deterioration using Bayesian
546 geoaddivitive regression model." *Journal of Infrastructure Systems*, 25(3), 04019021.
547

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.
550

551 Boxall, J., Saul, A., and Skipworth, P. (2004). "Modeling for hydraulic capacity." *Journal-American Water
552 Works Association*, 96(4), 161-169.
553

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.
557

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.
560

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, Sheffield,
563 UK.
564

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.
569

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/](https://www.ikt.de/blog/neuer-bildreferenzkatalog-zu-schaeden-an-privaten-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." *Applied clay science*, 42(3-4), 356-362.
704

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 Kutylowska, M., and Hotłoś, 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., Breyse, 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.

878

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.

881

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.

884

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.

889

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

892

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.

895

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

898

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.

903

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.

906

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.

909

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.

912

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.

915

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.

918

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.

921

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." *KSCCE*
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 Siedlungsentswässerung [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.
 978
 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.
 981
 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.
 984
 985 WRc. (2013). Manual of Sewer Condition Classification. 5th Revised Edition. WRc Publications.
 986
 987 WRc. (2021). Sewerage Risk Manual. Available at: <http://srm.wrcplc.co.uk/home.aspx> [Accessed
 988 22/09/2021].
 989
 990 Younis, R., Knight, M., Kleiner, Y., Matthews, J., and Jung, J. (2015). "Drinking water pipelines defect coding
 991 system." *Pipelines 2015*, 1110-1124.
 992
 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.
 996

997 **List of Figure Captions**

998
 999 **Figure 1:** Schematic describing the factors which can control the deterioration of buried water supply pipes

1000
 1001 **Figure 2:** Optimal dataset required for key asset characteristics of water and wastewater networks

1002
 1003 **Figure 3:** Optimal environmental dataset for buried assets of water and wastewater networks

1004
 1005 **Figure 4:** Conceptual relationships between asset condition, system performance and times to attain
 1006 unacceptable levels of performance

1009 **Tables**

1010

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

1013

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), (46) Wang et al. (2010), (47) Wang et al. (2009), (48) Watson et al. (2004), (49) Wood and Lence (2009), (50) Zhou et al. (2009), (51) Ana et al. (2009), (52) Bakry et al. (2016), (53) Balekelayi and Tesfamariam (2019), (54) Chughtai and Zayed (2008), (55) Davies et al. (2001), (56) Gedam et al. (2016), (57) Harvey and McBean (2014), (58) Kabir et al. (2018), (59) Khan et al. (2010), (60) Koo and Ariaratnam (2006), (61) Laakso et al. (2018), (62) Le Gat (2008), (63) Lubini and Fuamba (2011), (64) Mashford et al. (2011), (65) Micevski et al. (2002), (66) Mohammadi et al. (2019), (67) Najafi and Kulandaivel (2005), (68) Salman and Salem (2012), (69) Sousa et al. (2014), (70) Tran et al. (2006), (71) Tran et al. (2009), (72) Tran et al. (2007), (73) Wirahadikusumah et al. (2001).

DR: Data Requirements

Key: ↑ High, ↔ Medium, ↓ Low

Usages: (WS) Water Supply, (WW) Wastewater

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

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

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

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

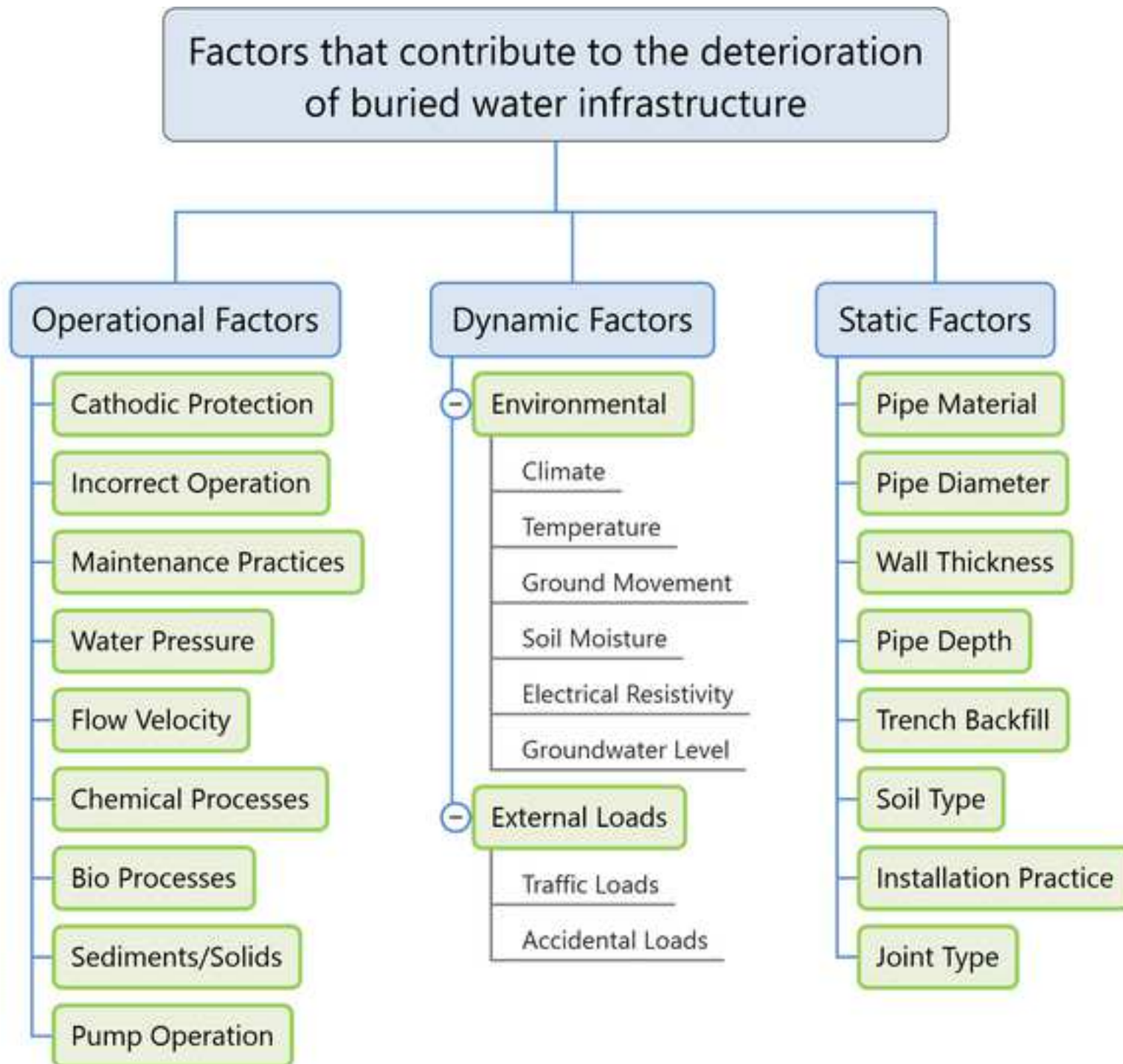


Figure 2 :Optimal dataset required for key asset characteristics of water and wastewater networks

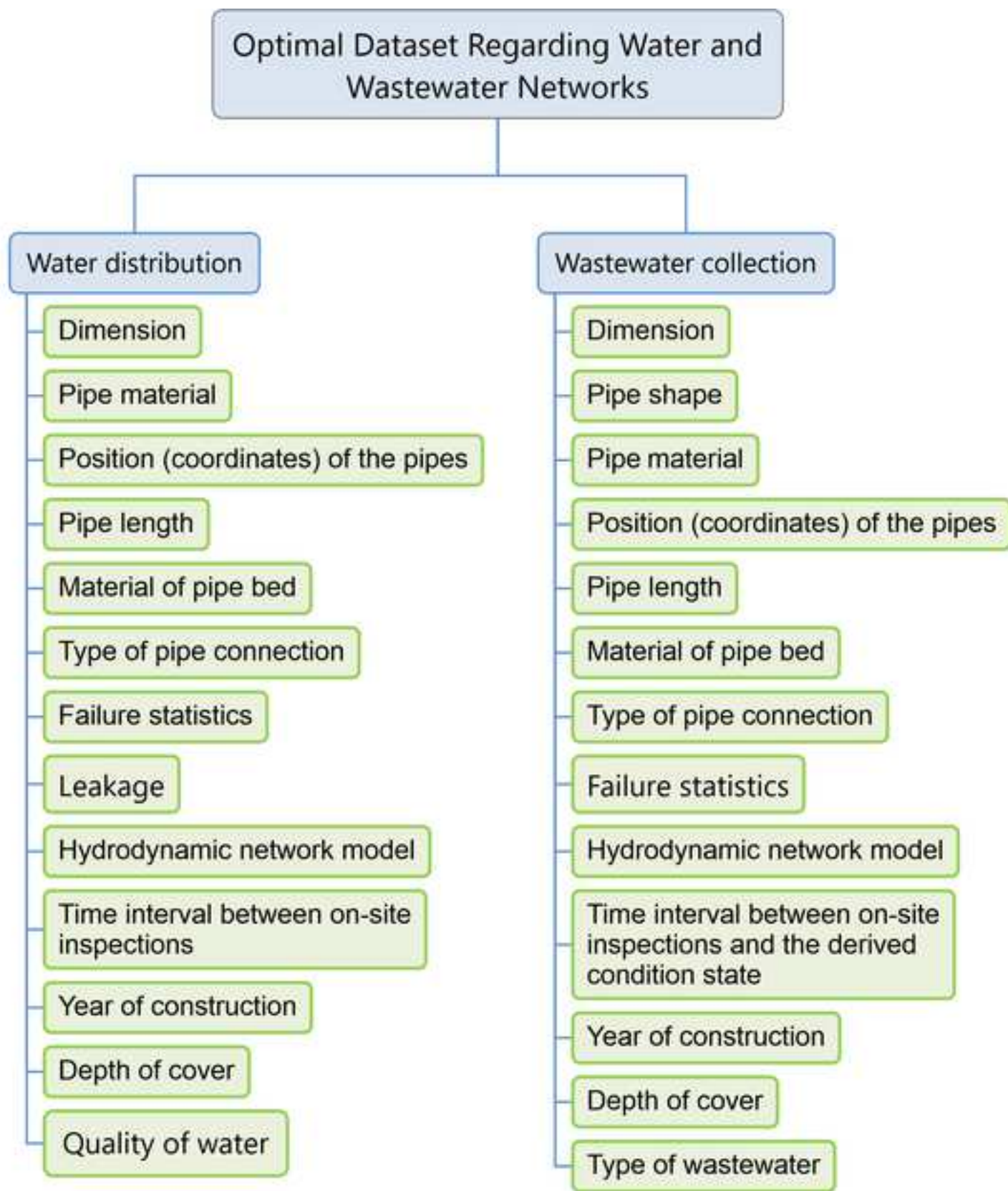


Figure 3: Optimal environmental dataset for buried assets of water and wastewater networks

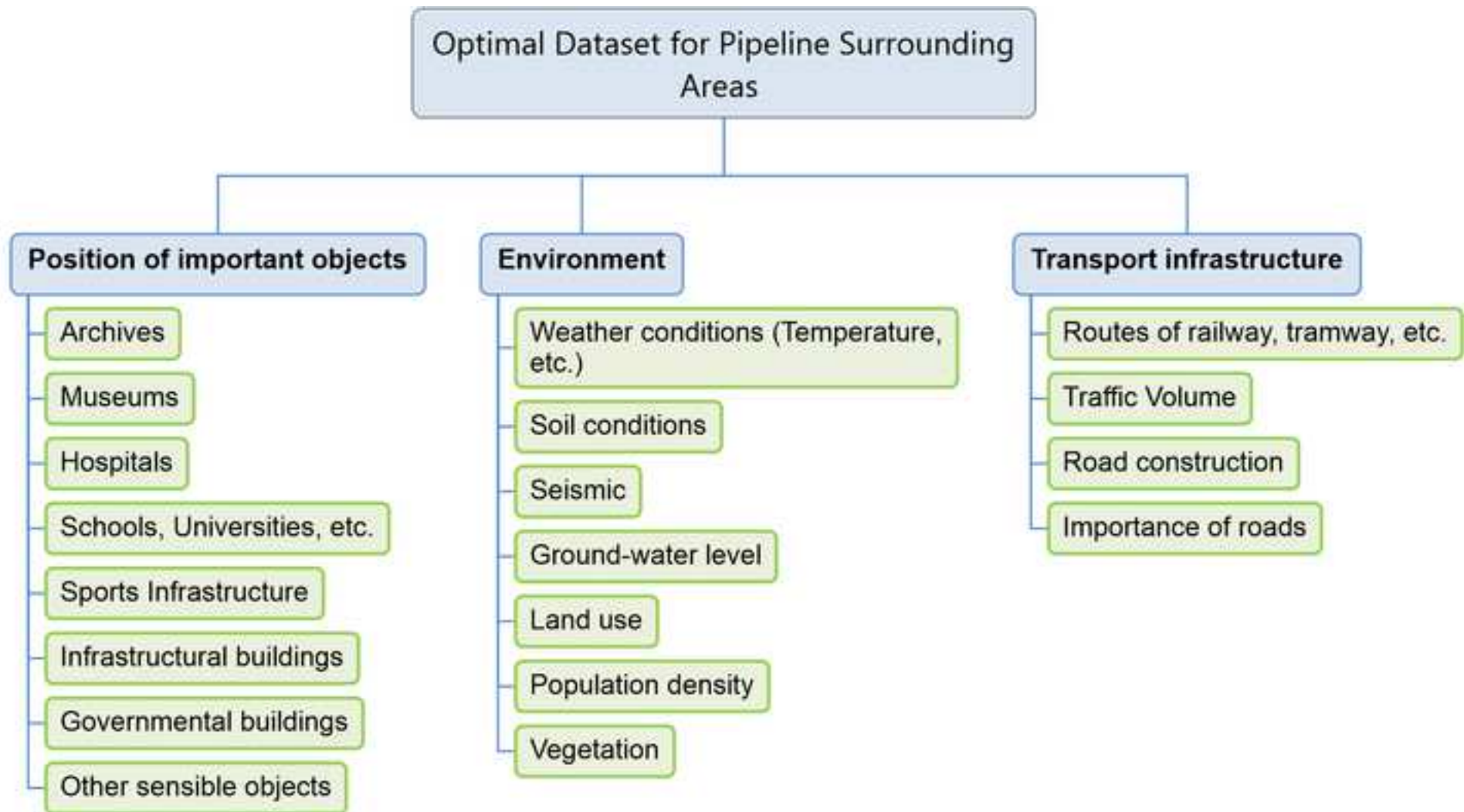


Figure 4: Conceptual relationships between asset condition, system performance and times to attain unacceptable levels of performance

