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Toward Sustainable Water Infrastructure: The State-Of-The-Art for Modeling the Failure Probability of Water Pipes

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Key Points:

- The state-of-the-art of failure modeling of water pipes is demonstrated
- A conceptual framework for decision-making process in water utility management is presented
- Key future directions for achieving more sustainable water distribution networks are discussed

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Abstract Failures of water distribution networks (WDNs) are rising at an exponential rate, necessitating immediate attention. An effective way to reduce the failure rate is to develop accurate predictive models for the failure probability of water pipes, which are the most critical assets of WDNs. Despite the fact that researchers have invested efforts to develop various predictive models, the extant literature lacks a complete state-of-the-art review. To fill this gap, this study employs a mixed approach (i.e., quantitative and qualitative) by providing (a) a bibliometric analysis of existing scholarly literature, (b) a systematic review of the techniques used in modeling the failure probability of water pipes, including physical, statistical, and machine-learning (ML)-based models, and (c) identified gaps and future research directions. The bibliometric analysis shows that ML-based models are emerging and, hence understudied as compared to the physical and statistical-based models. Regarding the systematic review, a proper understanding of the development of each model has been provided in addition to their advantages and critiques. Furthermore, failure probability integration methods are discussed. Findings reveal that the social and operation-related predictors have been understudied, thereby suggesting their further exploration. This study adds to the existing body of knowledge by providing water utilities and academics with a comprehensive understanding of the probability of water pipe failure, which will be useful in the decision-making process and network management.

Plain Language Summary This study is motivated by the lack of a comprehensive review of existing models in predicting the failure probability of water pipes. In order to fill this gap, this study conducts a bibliometric and systematic review by critically analyzing the physical, statistical, and machine learning-based models in the literature. A frequency analysis of the factors used in the development of the models was conducted, to determine the most influential factors. This research provides a complete reference for water utilities and academics on the prediction of water pipe failure, which would be useful in the decision-making process.

1. Introduction

Water distribution networks (WDNs) are undoubtedly a critical part of water utility assets, as they are responsible for water transmission (Atef et al., 2016; Berardi et al., 2014). It has been reported that, on average, 80% of water utility expenditures are spent on the management of WDNs (Poulakis et al., 2003). However, available evidence shows that the failure of WDNs is increasing at a fast rate, which negatively impacts individuals' social, economic, and health status (Steffelbauer et al., 2022; Yazdani & Jeffrey, 2012).

In the USA and Canada, around 700 water pipes fail daily, thereby contributing to the loss of over 2 trillion gallons of clean water annually (Fan et al., 2022). In 2017, more than 2.2 billion m^3 of water was loss in China (Liao et al., 2021). The enormous financial commitment associated with the failure of water distribution networks cannot be overemphasized. According to the American Water Work Association (AWWA), the USA needs to invest around $1 trillion in replacing and repairing the deteriorating components of their WDNs (Fan et al., 2022). In Australia, the estimated cost of repairing and maintaining WDNs is about AUD 1.4 billion (Weeraddana et al., 2020). In South Korea, 52.5% of the water pipes will require rehabilitation by 2024, as indicated in a study by Seo et al. (2015). In the case of Colombia, a developing country, approximately 50% of water is lost due to water pipe failures (Giraldo-González & Rodríguez, 2020). From the aforementioned, the failure of WDNs, which mostly consist of water pipes, is a global issue that requires utmost attention.

WDNs are founded underground; therefore, these infrastructures need to be designed to resist traffic, soil, internal, and overburden pressures, and other environment and operation related loads (Berardi et al., 2008). In essence, the reliability of WDNs must not be compromised during their service life; hence, catastrophic failure

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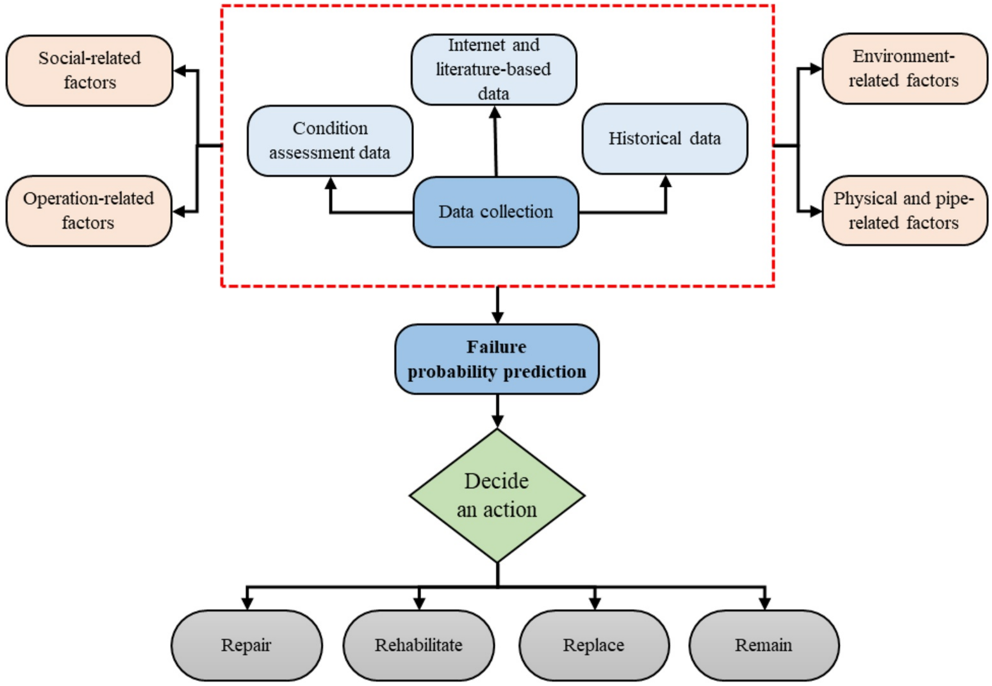

Figure 1. Conceptual framework for decision-making process regarding failure probability of water pipes.

may occur. Failure of WDNs causes not only water losses but also has a significant detrimental influence on other infrastructures such as road and sewage networks (Abdel-Mottaleb et al., 2019; Mazumder et al., 2021; Myrans et al., 2018). As a result, it is essential to prevent the occurrence of such incidents rather than respond to them when they occur.

In fact, certain water utilities throughout the world have been reported to replace a particular percentage of their pipeline network yearly based on an estimated guess owing to the fear of water pipe failure (Fitchett et al., 2020). Without a doubt, this strategy is less cost-effective and inefficient since some of the pipes will be removed despite the fact of their ability to operate for several more years. Therefore, understanding the failure mechanism and variables influencing water pipe failure will be critical for water utilities. In view of this, a conceptual framework that would assist utility managers in their decision-making process regarding the failure probability of water pipes is presented in Figure 1.

As illustrated in Figure 1, the first stage of making a decision in relation to pipe management is data collection. The data can be classified into three: condition assessment, Internet and literature-based, and historical data. From these data, four categories of factors affecting water pipe failure can be extracted—physical and pipe-related, environment-related, operation-related, and social-related factors—which serve as predictors (i.e., explanatory variables) for model development. Subsequently, predictive models for the failure probability of water pipes are developed. It should be noted that the quality and quantity of the data play a significant role in the models' accuracy. The outcome of the models (i.e., failure probability) will give an insight to the utility management on whether to repair, rehabilitate, replace or do nothing to a pipe. A pipe can be repaired so that it can continue to be used for its intended purpose (i.e., water transmission). Rehabilitation refers to the process of restoring a pipe close to its original condition to extend its useful life (Ganesh & Murthy, 2019). On the other hand, replacement is the act of changing the pipe with a new one.

Having noted that, researchers have developed various models for predicting the probability of water pipe failure. These models can be broadly categorized into physical, statistical, and machine learning (ML) models. In physical models, the physical deterioration mechanism of the water pipe is taken into consideration, and the models are built on the basis of making a comparison between the pipe's resistance and stresses exerted on such pipe. In the case of statistical-based models, the failure data of a network is analyzed using statistical laws and theorems. ML-based models are developed by intelligently recognizing certain patterns from the historical and maintenance data of a network.

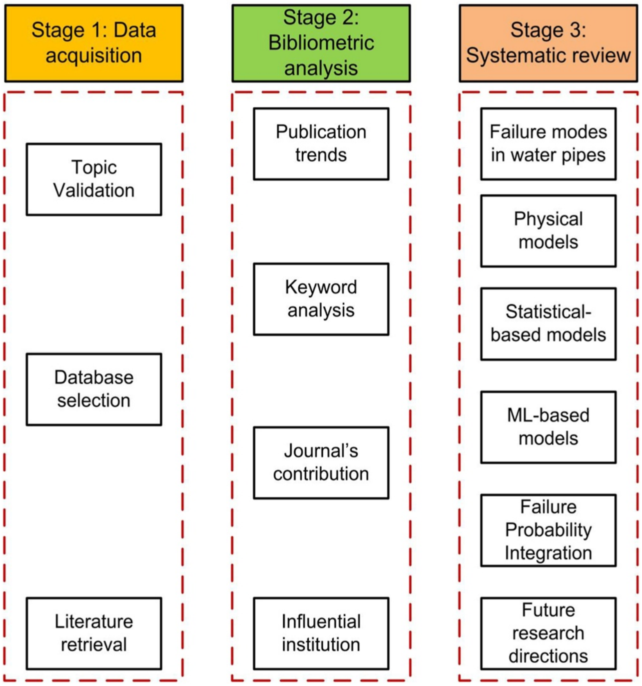

Figure 2. Research framework.

General reviews on physical and statistical models for predicting water mains were conducted in the last two decades (Rajani & Kleiner, 2001a, 2001b). Furthermore, the review paper by Wilson et al. (2017) focuses solely on statistical models applicable to large-diameter pipes, despite the fact that more than 90% of water pipes in most water utilities consist of small diameter pipes (<300 mm) (Chik et al., 2017). Scheidegger et al. (2015) presented a comprehensive review of nine statistical failure models for WDNs. In addition, Ogutu et al. (2017) reviewed probabilistic modeling that use the Bayesian network to model the failure rate of water pipes. Therefore, the literature lacks a comprehensive and holistic review of all the three modeling categories for predicting the failure probability in water pipes. Hence, this study aims to review the existing literature on modeling the failure probability of water pipes. The following are the study's particular objectives:

1. Providing a bibliometric analysis of existing studies on the failure probability of water pipes, including the publication trends, keyword analysis, and scientific mapping of research outlets and influential institutions.
2. Conducting a systematic review of the techniques used for modeling the probability of water pipe failure, including physical, statistical-based, and ML-based models.
3. Identifying the gaps and providing future directions to fill them.

2. Research Methodology

The research approach used in this study is a hybrid of quantitative and qualitative methodologies. The bibliometric analysis and systematic reviews represent the quantitative and qualitative methods, respectively. The hybrid methods are adopted to overcome the limitation associated with the "mono review method," such as bias in selecting research papers and a lack of holistic view of a research domain (Khodabandelu & Park, 2021; Pluye & Hong, 2014). As a result, the study involves three main stages, as shown in Figure 2. The first stage entails data acquisition, in which the processes adopted for retrieving the relevant literature for this study are illustrated in Figure 3. First, the topic validation

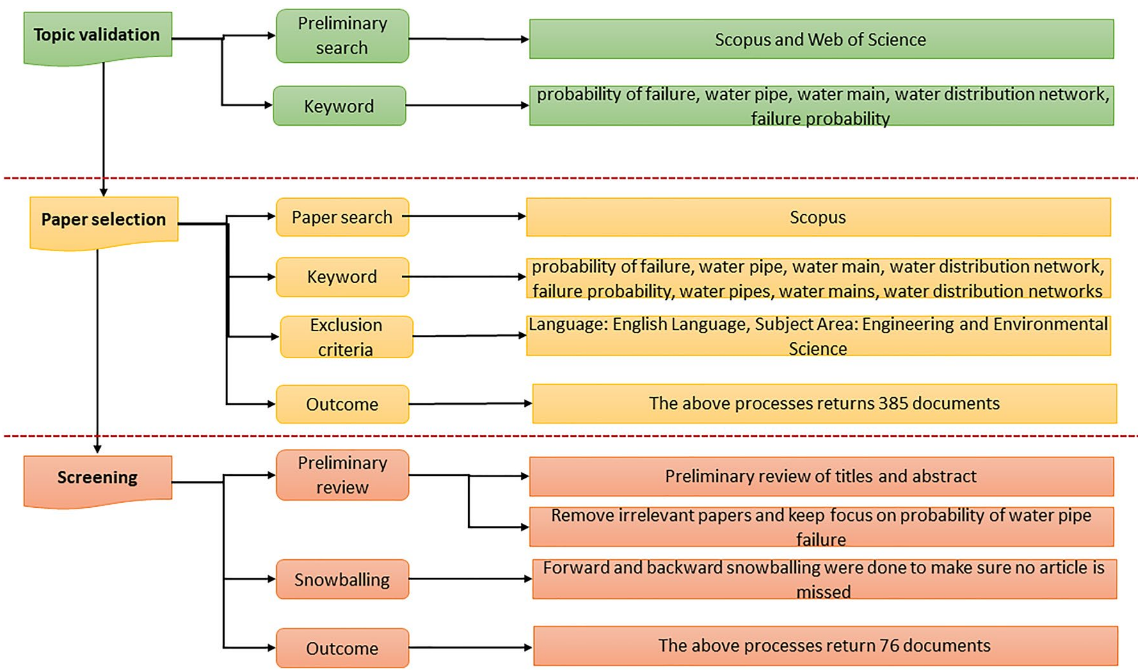

Figure 3. Literature retrieval methodology.

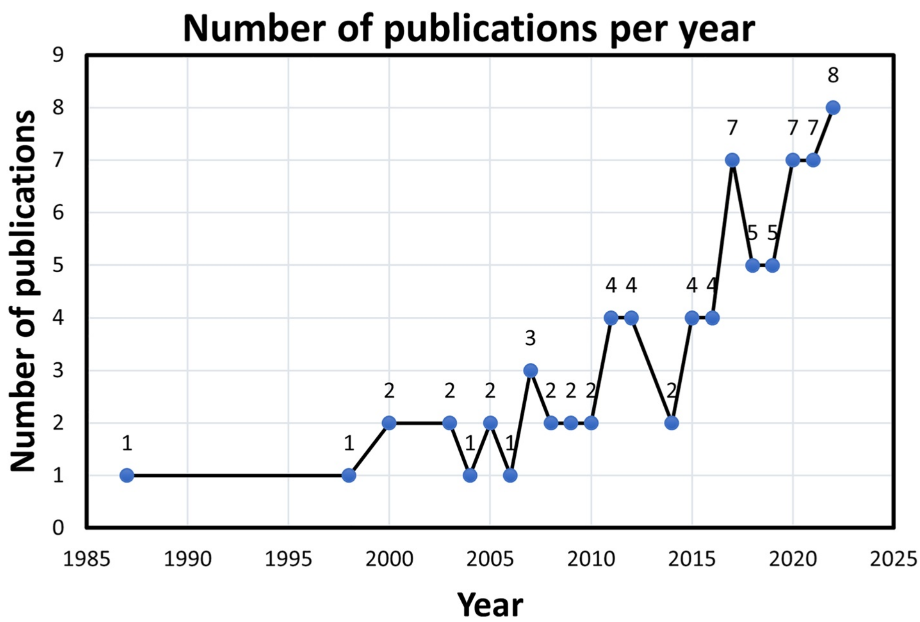

Figure 4. Trends in research publications.

was conducted by carrying out a preliminary search through the "Scopus" and "Web of Science" databases to ascertain the necessity of this research. Subsequently, "Scopus" was selected for the literature retrieval since it is the largest academic database with recent publication coverage (Debrah et al., 2022). After defining the exclusion criteria, as shown in Figure 3, the search string returns 385 documents. These documents were forwarded to the following step, where a preliminary evaluation of abstracts and snowballing were performed. Snowballing is the process of identifying additional papers to include in the review. The two types of snowballing were adopted: forward and backward snowballing. Forward snowballing involves searching for papers that cite the paper being examined, while backward snowballing involves checking the reference list of the examined paper to find other relevant research articles. This process ensures no related paper was omitted. The outcome of these processes produced 76 research papers.

The second stage of this study involves carrying out a bibliometric analysis of the selected research papers. Bibliometric analysis is a method of mapping and visualizing a scientific data set to portray the state-of-the-art in a certain topic. In view of this, the bibliometric analysis was conducted to identify the publication trend, keyword analysis, and the contribution of research outlets and influential institutions. The last stage comprises the systematic review, which is a methodical approach to recognizing the contribution of scientific literature to a particular domain and identifying the knowledge gaps in such research fields. According to the systematic review, the techniques adopted in modeling the failure probability of water pipes can be categorized into three groups: physical, statistical-based, and ML-based models.

3. Bibliometric Analysis

As previously stated, this research employs bibliometric analysis to identify the trend in the annual publication, keyword analysis, and the contribution of research outlets and influential institutions in the domain of water pipe failure probability prediction. Although various tools are available for conducting a bibliometric analysis, VOSviewer was chosen for this research because it is straightforward and produces strong bibliometric networks (Debrah et al., 2022). Moreover, VOSviewer is open-source software.

3.1. Publication Trends

Figure 4 shows the annual publishing trends for the scholarly literature in the domain of failure probability of water pipes. As per the articles included in this study, the publication year ranged from 1987 to 2022. It can be seen that only two articles were published before the year 2000. This either shows that minimal efforts were

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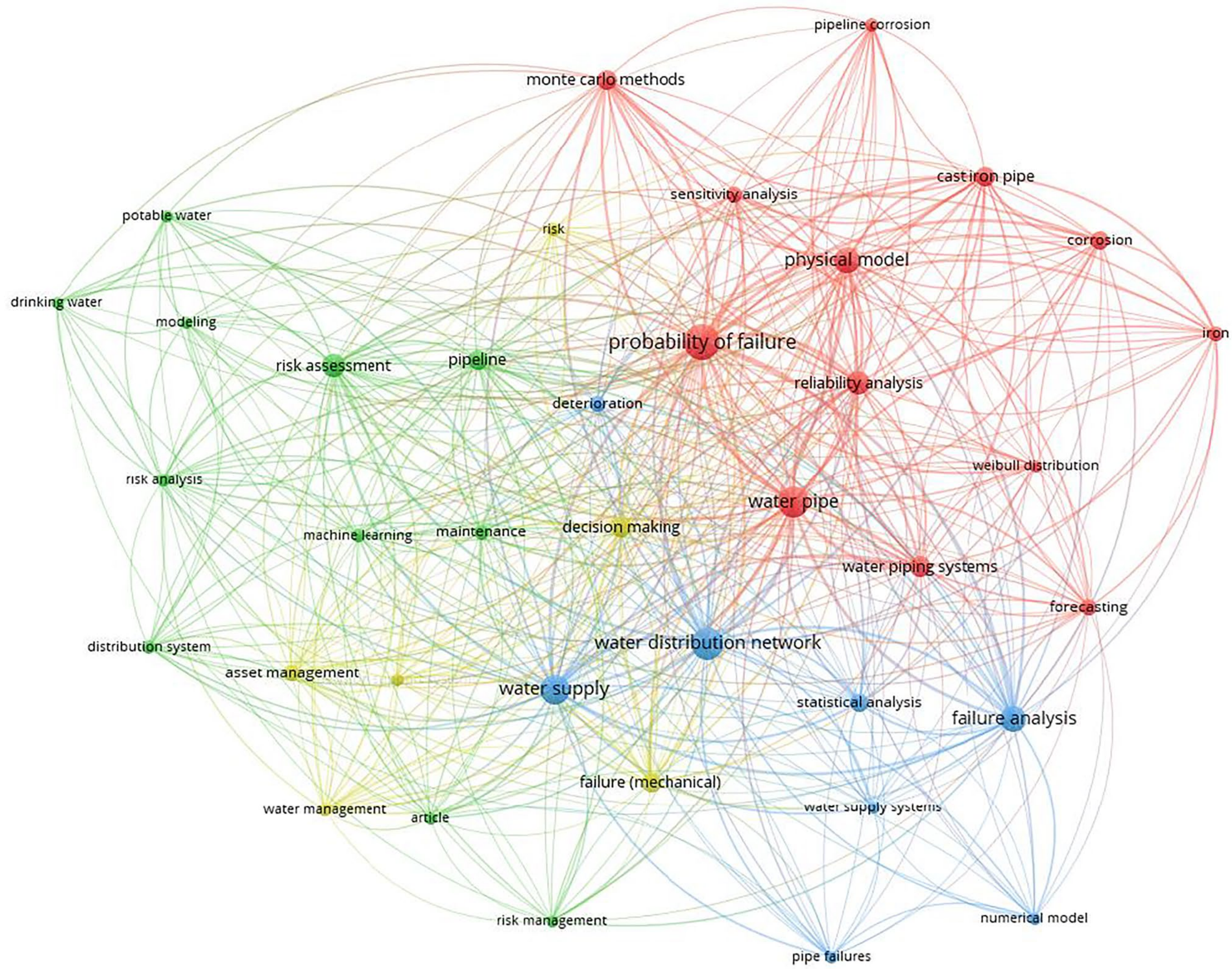

Figure 5. Keyword co-occurrence network.

paid to this domain in the last century, or the problem was not significant as the pipes were not aged. This could be attributed to the limited robust technologies and tools for developing predictive models in this era (Aryai et al., 2022). Another reason may be the lack of sophisticated digital tools or platforms to showcase the conducted research in this era (i.e., before 2000). From 2000 to 2010, the overall number of publications was 17, whereas from 2011 to 2020, the total number of publications was 42. This implies that the field is emerging as the number of publications increases from one decade to another. Although only 15 articles have been published in 2021 and 2022, it is expected that the number will exceed that of the previous decade by the end of 2030. This is due to the fact that many utilities are taking proactive measures to construct prediction models for their WDNs (Weeraddana et al., 2020). Furthermore, the emergence of ML-based models may promote further growth in this domain's publishing.

3.2. Keyword Co-Occurrence Analysis

Keyword co-occurrence analysis is an important aspect of bibliometric analysis, as it gives insight into the links between research areas within a specific domain. Using VOSviewer, the "minimum number of occurrences" requirement was set to 5; 38 keywords satisfied this condition (Van Eck & Waltman, 2010). However, it was observed that some of these keywords express the same meaning; hence, they were merged using the "Thesaurus file function" of the software. For instance, the keywords "risks" and "risk" were merged. According to Figure 5, three clusters are observed from the mapping network. The red cluster is dominated by "probability of failure,"

Table 1
Keyword Co-Occurrence and Total Link Strength

Keyword	Occurrences	Total link strength
Probability of failure	37	212
Water distribution network	29	165
Water pipe	28	162
Water supply	26	157
Physical model	19	120
Failure analysis	20	113
Reliability analysis	16	105
Risk assessment	16	104
Decision making	13	90
Water piping systems	13	87
Pipeline	12	86
Cast iron pipe	12	82
Failure (mechanical)	12	81
Monte Carlo methods	11	78
Corrosion	10	62
Statistical analysis	10	54
Asset management	8	53
Maintenance	7	51
Forecasting	8	50
Iron	7	50
Risk analysis	6	50
Water management	6	49
Sensitivity analysis	8	48
Deterioration	8	43
Weibull distribution	5	43
Machine learning	6	42
Decision support systems	5	41
Pipeline corrosion	6	40
Risk	6	37
Distribution system	6	35

whereas the blue and green clusters are dominated by "water distribution network" and "risk assessment," respectively. The proximity of each node to one another indicates the strength of their relationship. For example, because their nodes are adjacent, the strength between "probability of failure" and "reliability analysis" is significant (see Figure 5). Table 1 reports the top 30 keyword occurrences and their respective total link strength. This evidences that the selected articles to be reviewed in this study are highly representative of the domain, where "probability of failure" and "water pipe" are the most occurred keywords in the list. According to the frequency of occurrences and total link strength, "physical models" are well-researched in the literature compared to "ML" models. Furthermore, it is also observed that "cast iron (CI) pipe" is the most investigated water pipe type. In this context, a link refers to the co-occurrence of two keywords in a publication. The strength of the link is represented by a positive numerical value, with a higher value indicating a stronger association between the two keywords. As presented by the developers of VOSViewer, the formula for calculating the link strength can be found in Equation 6 in van Eck and Waltman (2009). The total link strength denotes the number of publications in which the two keywords appear together.

3.3. Journals' Contributions

Table 2 lists the top 10 research outlets as per the scope of this study. This sort of analysis is beneficial for readers who want to know where to source information related to a particular research focus. Furthermore, it can provide insights into how institutional and commercial libraries allocate journal subscription funds based on their research interests. Using VOSviewer, the analysis type was set as "citation," and the unit of analysis was "sources." Even though there is no limit for the "minimum number of documents" and "minimum number of citations," these requirements were set to 2 and 25, respectively, for generating the optimal network after multiple attempts. Besides, this threshold limit was also in agreement with past studies (Tariq et al., 2021). Table 2 shows that "Reliability engineering and system safety," and "Water research" are the most productive journal in terms of the number of citations, documents, and total link strength. The table also reveals that, despite the fact that "Journal of water supply: research and technology - aqua" and "Journal of infrastructure systems" have five and four articles published, the citations of "Journal of hydroinformatics" and "Journal of water resources planning and management" with 3 research papers are higher.

3.4. Influential Institutions

The co-authorship of organizations is another necessary sort of bibliometric analysis performed in this study in order to know the most collaborative institutions in the domain of water pipe failure probability predictions. This will also be helpful for individuals or organizations interested in researching the failure probability of water pipes to know who they can collaborate with effectively. The analysis type was set to "co-authorship," and the unit of analysis was set to "organizations." The "minimum number of documents" and the "minimum number of citations" were set to 1 and 25, respectively. 61 out of 149 institutions qualified for these criteria, and the top 10 are presented in Table 3. According to the results, "Université Laval, Canada," "McGill University, Canada," "Eawag:Swiss federal institute of aquatic science and technology, Switzerland," and "University of British Columbia, Canada" are the most collaborative institutions, with each exhibiting a total link strength of 4. Furthermore, the results show that few institutions in Canada, Switzerland, Australia, and Spain have established some collaboration with other institutions. To achieve a high standard in combating the increasing failure rate of water pipes through the development of robust predictive models, institutions across the globe should collaborate

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Table 2
Journals Contributions

Source	Documents	Citations	Total link strength
Reliability engineering and system safety	8	319	11
Water research	5	303	12
Journal of hydroinformatics	3	204	8
Journal of water resources planning and management	3	150	12
Journal of water supply: research and technology - aqua	5	124	3
Water resources research	2	99	7
Engineering failure analysis	3	47	1
Journal of infrastructure systems	4	36	6
Urban water journal	3	34	8
Journal of pipeline systems engineering and practice	2	31	2

with each other so they can benefit from diverse knowledge and experience, as this is currently lacking in the scholarly literature.

4. Findings From the Systematic Review

The systematic review findings, which centers on the adopted techniques for predicting the failure probability of water pipes are presented. Figure 6 illustrates the proposed classification of the techniques, which involve the physical, statistical, ML, and the combined models. While physical, statistical and ML-based models are discussed in detail in subsequent sections, limited information is available in relevant literature on the fourth classification: combined models. However, it is highlighted in Figure 6 to demonstrate the feasibility and effectiveness of the method. These combined models can also be referred to as surrogate models. For water pipe failure probability estimation, a surrogate model can be made by accurately approximating a complex system by integrating data (usually less than the required data needed to understand the behavior of a complex system) from physical model to an ML model and subsequent embed it in a statistical probabilistic method such as crude Monte Carlo simulations. Prior to explaining the techniques for predicting the failure probability of water pipes, a brief explanation of water pipe failure modes is presented.

4.1. Failure Modes in Water Pipes

Failure modes refer to the exact way at which an asset fails (Barton et al., 2019). Hence, water pipes can exhibit failure in different modes. It should be noted that the prediction of failure probabilities of water pipes through

Table 3
Influential Institutions

Organization	Documents	Citations	Total link strength
Université Laval, Québec City, Canada	1	132	4
McGill University, Montreal, Canada	1	35	4
Eawag: Swiss Federal Institute of Aquatic Science and Technology, Switzerland	3	166	4
University of British, Columbia, Kelowna, Canada	1	32	4
Monash University, Melbourne, Australia	1	55	3
RMIT University, Australia	1	33	3
Swinburne University of Technology, Australia	1	33	3
Rajani Consultants Inc., Ottawa, Canada	1	33	3
Southwest Petroleum University, China	1	29	3
Universidad Politécnica de Valencia, Valencia, Spain	1	32	2

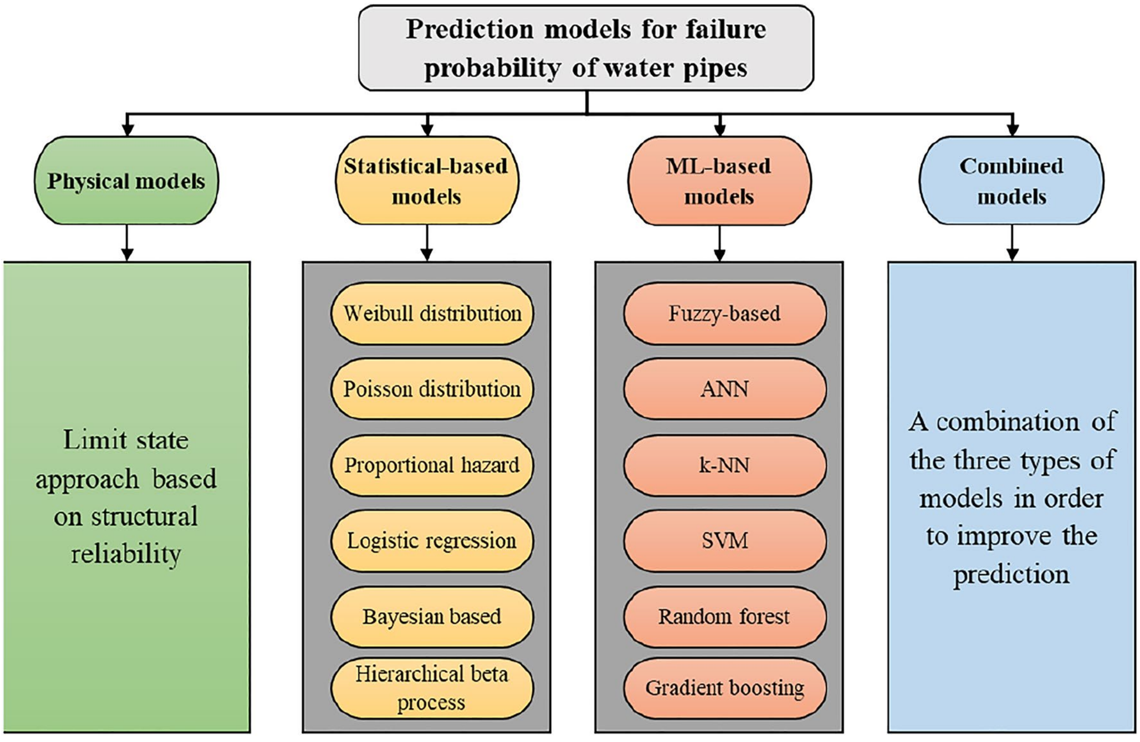

Figure 6. Prediction models for failure probability of water pipes.

various modes is mostly done using the physical models. A limit state function (LSF) is usually formulated for each failure mode. However, statistical and ML models can estimate the failure probability of each pipe for different failure modes if the relevant historical data are available. For instance, the historical data can specify when a pipe fail due to leakage, burst, or flexural bending, and amongst others. The most common failure modes of water pipes are briefly discussed below.

- **Leakage:** This failure mode occurs as an operational hazard, which does not only lead to loss of water but also reduce the inner pressure (Wang et al., 2021). Leakage has been attributed to poor joint installation and clogging (Clair & Sinha, 2014).
- **Burst:** This failure mode occurs when the material experience rupture due to excessive internal pressure and corrosion defects (Wang et al., 2021).
- **Collapse:** Similar to "burst" failure mode, a pipe is said to collapse when it fails due to external pressure exerted on it. The failure mode is associated with stiffness loss and local instability (Gouveia et al., 2020).
- **Deflection:** This failure mode occurs when the vertical diameter of a pipe is decreased. According to the American Water Work Association, defection of pipes is associated with pipe-soil interaction, external load, and stiffness of the pipe (Shuai et al., 2017). Different deflection limits are assigned to different materials. For instance, the critical defection value for steel pipes is 5% (Wang et al., 2021).
- **Bending**: This is also referred to as "flexural failure mode," and it occurs when the bending stress exerted on a pipe exceeds its critical value. The maximum allowable bending stress of a pipe usually occurs at its mid-length.
- **Corrosion pit:** This type of failure mode is associated with the metallic pipes. This failure mode occurs when holes are created at a localized region on the pipe due to loss of metal (Farh et al., 2022; Grigg, 2017).
- **Circumferential cracking:** This occurs when a pipe cracks at its circumference (Fuchs-Hanusch et al., 2014). This type of failure is typically caused by bending moments on the pipe, which can be caused by external forces such as frost penetration, backfill, and inadequate bending conditions.

To prevent or mitigate these failure modes, water pipeline operators can take a number of steps. For example, regular inspections and maintenance can help to identify and address potential problems before they become serious. In addition, the use of corrosion-resistant materials and protective coatings can help to reduce the risk of corrosion. Additionally, proper installation techniques and quality control measures can help to ensure that water pipelines are installed correctly and are able to function properly over time (Grigg, 2017).

5. Physical Models

Researchers in this domain have invested enormous efforts in modeling the failure probability by considering the pipes' physical failure mechanism. Table 4 gives a summary of the reviewed physical models, including the authors, the employed methodology, model accuracy (if available), validation status, failure mode, the most important factors considered, the used data type, and the pipe material. It should be noted that the "most important factors considered" refer to the critical factors affecting the failure probability in each study (where applicable), which are determined from a sensitivity analysis, correlation analysis, or relative importance analysis.

5.1. Limit State Equations Based on Structural Reliability

During the development of a physical model based on reliability theory, a LSF is defined by comparing the capacity of a pipe with the stress exerted on it. Equation 1 states a typical LSF, where LSF violation will result in a pipe's failure. Thus, the probability of water pipe failure can be represented by Equation 2 (Mahmoodian & Li, 2018). It should be noted that the LSF can be defined based on different failure modes such as burst, leakage, longitudinal deflection, etc. (Davis et al., 2008; Wang et al., 2021). Furthermore, the LSF can be transformed into a factor of safety (FoS) to define the failure criteria of pipes (Sadiq et al., 2004). An FoS of more than 1 indicates that the pipe is safe and has no failure, while an FoS of less than 1 shows that the pipe's capacity has been exceeded and, thus, is considered failed. In terms of quality-based assessment, a partial FoS is derived by comparing the load exerted on the pipe to its resistance.

$$G(S, L, T) = L(T) - S(T) \tag{1}$$

$$P_f = p[L(T) - S(T) \leq 0] \tag{2}$$

where LSF is represented by $G(S, L, T)$, L denotes the capacity of a pipe, S represents the exerted stresses on the pipe, T refers to the time, p denotes the probability of LSF violation, and P_f denotes the failure probability. Therefore, if $G(S, L, T) > 0$ the pipe is considered as safe, while failed if $G(S, L, T) \leq 0$. In most studies, the failure probability (i.e., Equation 2) is estimated using a structural reliability analysis technique such as simulation approaches (i.e., Monte Carlo Simulation, MCS) or analytical approaches (i.e., First Order Reliability Method, FORM). However, MCS is the most adopted approach in scholarly literature due to its ability to deal with complex problems such as the failure of water pipes (Padmanabhan et al., 2006). Further details on MCS can be found in the study of Rubinstein and Kroese (2008). In this method, the variables formulating the LSF are randomly selected and employed to evaluate its outcome. If the LSF is violated, the pipe will fail; otherwise, no failure event will be recorded. This process requires a large simulation number (e.g., over 10,000 simulations) (Punurai & Davis, 2017; Wilson et al., 2015) to estimate the failure probability by using Equation 3.

$$P_f = \frac{n}{N} \tag{3}$$

where n is the number of times the LSF is violated, and N is the total number of simulations.

As seen in Equation 1, the LSF comprises two components: resistance of the pipe to failure and exerted stresses on the pipe. The two components of LSF for previous studies are shown in Table 5.

Mahmoodian and Aryai (2017) investigated the failure probability of corroded steel water pipes. The non-linearity of corrosion was taken into consideration based on the Power Law model (Romanoff, 1957) using Equation 4.

$$\Delta = at^b \tag{4}$$

where Δ denotes the corrosion depth at a time "t," "a," and "b" could be determined from the analysis of the inspection data.

In order to achieve a high level of prediction accuracy, 10,000 simulations were considered, as the sample size has a significant effect on the accuracy of MCS results. More importantly, six failure modes (i.e., limit states) were considered: buckling, ring deflection, longitudinal deflection, flexural, wall thrust, and burst. The flexural

Table 4
Summary of the Physical Models

Authors	Methodology	Validated?	Failure mode	Accuracy	The most important factors considered	Type of data	Material type
Mazumder et al. (2021)	Limit state equations + MCS	No	Collapse	–	–	Field data	CI
Wang et al. (2021)	Limit state equations + MCS	No	Leakage, burst, deflection, and bending failure	–	–	Field data	CI
W. Li et al. (2021)	Finite element analysis and MCS	Yes	Burst	–	Pipe thickness, internal pressure, traffic	Literature-based + field data	CI
Mady (2021)	Limit state approach + MCS	No	Collapse	–		Field data	Concrete
Aryai et al. (2020)	Finite element modeling + copula method	Yes	Corrosion pit and collapse	–	Diameter, wall thickness	Field data	CI
Zhang et al. (2019)	Limit state equations + MCS	No	Corrosion pit, burst, and rupture	–	Radial corrosion rate, axial corrosion rate	Literature-based	Steel
Mahmoodian and Li (2018)	Limit state equations + MCS	No	Corrosion pit	–	Wall thickness, corrosion depth	Literature-based + field data	CI
Phan et al. (2018)	Limit state equations + MCS + Weibull distribution	No	Corrosion pit and burst	–	Wall thickness, loads, corrosion size	Literature-based data	–
Aryai and Mahmoodian (2017)	Limit state equations + MCS	Yes	Leakage, circumferential cracking, ring deflection, wall rupture, and buckling	15.6% (prediction error)	Length	Field data + historical data	CI
Mahmoodian and Aryai (2017)	Limit state equations + MCS	No	Bending, wall thrust, ring deflection, longitudinal deflection, leakage, and buckling	–	Corrosion factors	Field data	Steel
Punurai and Davis (2017)	Limit state equations + MCS	No	Burst and collapse	–	-	Field data + literature-based data	AC
Wilson et al. (2015)	Factor of safety analysis + MCS	No	Corrosion pitting and collapse	–	Diameter, buried depth	Field data + literature-based data	CI
Qian et al. (2013)	Limit state equations + FITNET FFS procedure + MCS	Yes	Collapse	–	Tensile strength, crack depth, internal pressure	Literature-based	–

Table 4
Continued

Authors	Methodology	Validated?	Failure mode	Accuracy	The most important factors considered	Type of data	Material type
Jallouf et al. (2011)	Factor of safety analysis + MCS	No	Burst	–	–	Field data	CI, Steel, PVC
Qian et al. (2011)	FITNET FFS + limit state equations + MCS	No	Burst	–	Depth of defect, tensile strength, wall thickness	Field data + literature-based data	–
Davis et al. (2008)	Limit state equations + MCS	No	Burst and collapse	–	–	Field data	AC
De-Silva et al. (2006)	Limit state equations + FOSM	No	Corrosion pit	–	–	Field data	Steel
De Leon and Macías (2005)	Limit state equations + FOSM	No	Corrosion pit and burst	–	–	Field data	–
Davis et al. (2004)	Limit state equations + survival function + MCS	No	Corrosion pit	–	–	Field data	CI
Sadiq et al. (2004)	Factor of safety analysis + MCS	No	Corrosion pit and collapse	–	Corrosion depth	Literature-based + field data	CI

and wall thrust limit states were considered as a series system since the occurrence of any of the two limit states can cause failure. The other four states were considered as a parallel system since the occurrence of any of them could not cause the system to fail. Figure 7 shows the six modes of failure using the appropriate shapes in fault tress analysis to represents the top event (i.e., failure of water pipes), failure modes (i.e., basic events) and the logic gates. As known in the limit state reliability theory, the results from the study (Mahmoodian & Aryai, 2017) show that consideration of multiple limit states is essential in determining the failure probability of water pipes since different failure mechanisms contribute to overall pipe failure. For instance, the service life of a pipe was estimated to be 140 years when only the leakage limit was considered, whereas it was estimated to be 45 years when six limit states were considered (Mahmoodian & Aryai, 2017). This shows that consideration of only one

Table 5
Components of Limit State Functions and Driving Factors

Failure modes	Resistance	Stress	Driving factors	Reference
Longitudinal split	$\sigma_{f=\sigma_o-120\,\frac{(\mathrm{Age}\times\delta)}{b_o}}$	$W=(P_e+P_s)(D+b_o)$	Corrosion	Davis et al. (2004)
Pitting	$P_f=\frac{2\sigma_{\mathrm{uts}}\times t\times 0.5^{\frac{65}{\sigma_{ys}}}}{(D-t)}\times\left[\frac{1-\frac{d(T)}{t}}{1-\frac{d(T)}{t}\times Q^{-1}}\right]$	P_{op}	Corrosion	Qian et al. (2011)
Flexural failure	$M_n=\frac{2D_f E\Delta Y y_o S_{f1}}{D_m^2}$	F_y	Ground movement and external loadings	Gabriel (2011)
Ring deflection failure	$\Delta X=\frac{K\left(D_L W_c+P_s\right)D_m}{\frac{8EI}{D_m^3}+0.061E'}$	$\Delta X_{\mathrm{cr}}=0.05D_i$	Soil compression	BS 9295 (2010)
Buckling failure	$P=\frac{1}{S_f}\sqrt{\left(32R_w B' E_s\,\frac{EI}{D_m^3}\right)}$	$P_{\mathrm{cr}}=R_w\frac{w_c}{D_m}+\frac{p_s}{D_m}$	Elevated temperature	Moser and Folkman (2008)
Circumferential failure	σ_y	$p_f=\frac{P_{\mathrm{op}}\times D}{2t_w}+\sigma_b$	Internal pressure and bending stress	Phan et al. (2018)
Leakage failure	$S_{\mathrm{total}}=\sum\pi R_k^2$	S_{lim}	Corrosion	C. Li et al. (2017)
Wall thrust failure	$T_a=F_y(W_t-\Delta)\varnothing$	$T_{\mathrm{cr}}=1.3\,(1.67P_sC_L+P_W)\,\frac{D_o}{2}$	Traffic, hydrostatic and soil loads	Gabriel (2011)
Collapse pressure	$p_{\mathrm{total}}=\frac{\gamma_w}{1728}H_w+R_w\frac{w_s}{12D_o}+\frac{w_L}{144D_o}$	$p_{\mathrm{cr}}=\frac{1.2C_n\,(EI)^{0.33}\left(\varnothing_s E' k_v\right)^{0.67}R_H}{S_f r_o}$	External and internal loads	Wang et al. (2021)
Bending failure	$\sigma_{m=}\frac{(w_s+w_L)L^2}{8\pi[d-a(t)]r^2}$	σ_f	External loadings	Wang et al. (2021)

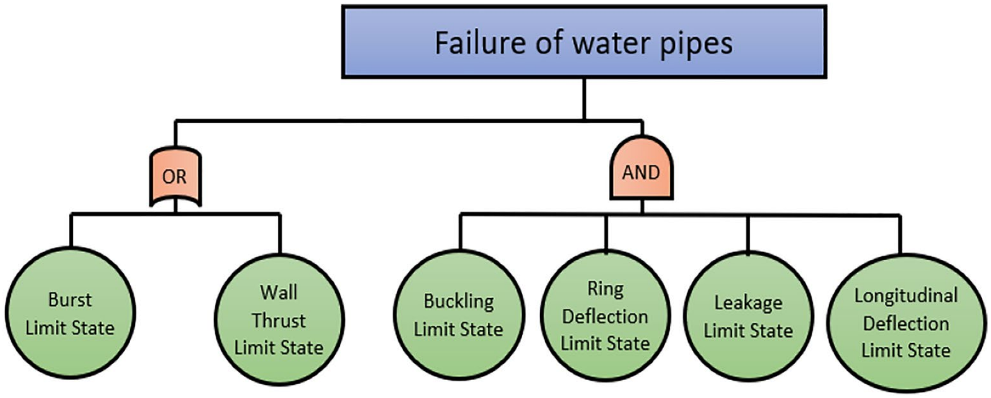

Figure 7. Multiple failure modes.

limit state can lead to inappropriate service life estimation, which may facilitate wrong decision-making in relation to pipe management.

While developing a risk index for water pipes located at Fairfield, California in the USA, Mazumder et al. (2021) adopted a physical probabilistic approach to generate a fragility curve (i.e., conditional probability of failure), MCS (10,000 samples) was used to deal with the uncertainty associated with stress calculation. Lognormal and normal distributions were used for the probabilistic analysis. The pipe capacity was estimated using the model of Ji et al. (2017), while the equation proposed by Robert et al. (2016) on exerted stress was adopted. The actual ages of the pipes in the network were assumed to range between 70 and 100 years. This may be inaccurate, as CI pipes have been used in the USA since the late 19th century. Similarly, the model does not consider any operation and environment-related factors apart from internal pressure and traffic loads, respectively. No sensitivity analysis was conducted on the input variables.

The First/Second Order Reliability Methods (FORM/SORM) are two analytical reliability methods that use the linear and quadratic approximations of the LSF to calculate the reliability index, which is then converted to failure probability. The efficiency of these approaches is determined by the complexity of the LSF (e.g., more applicable to less expensive and linear LSF) and the distribution of the random variables (e.g., FORM is applied when the variables follow a normal distribution) (Ben Seghier et al., 2020, 2022). Apart from FORM/SORM, First Order Second Moment Approximation (FOSM) is another approach that has been used to model the failure probability of water pipes. De Leon and Macías (2005) examined the effect of spatial correlation on the failure probability of corroded pipes using the FOSM method. Their results indicated that pipe segments adjacent to each other have a high correlation coefficient in terms of failure probability due to corrosion depths, while pipe segments far away, having two or more segments between them, had zero degree of correlation. However, the study assumes that failure occurs only due to internal pressure, serving as a limitation of the study. A similar assumption was made in the study of De-Silva et al. (2006).

While other research studies focused on the failure probability of CI pipes, the study conducted by Davis et al. (2008) focused on AC pipes. Unlike CI and other metallic pipes that undergo electrochemical corrosion, AC pipes' main degradation process is due to leaching corrosion as a result of contact with soft water. The uncertainty in the degradation mechanism of water pipes is complex and dynamic in nature. For example, the leaching rate in an AC pipe can differ across the pipe length due to changes in the water pH or other influencing factors. One way to handle this uncertainty is by defining the input parameters in form of a probability distribution. This promotes better understanding and facilitates accurate failure prediction.

Furthermore, it is essential to note that the spatial-temporal analysis of corroding pipes has received limited attention from researchers. Aryai and Mahmoodian (2017) used random field theory to determine the correlation length of corroded water pipes, which was used in the estimation of failure probability. The correlation length is the length at which a corroded surface can be said to exhibit uniform corrosion. That is, the lesser the correlation length, the more fluctuated the surface is in terms of corrosion. Although the prediction accuracy of their model is 84.4%, which is higher compared to other studies that do not consider the spatial relationship of corroding pipes, the accuracy can be improved if the probability distribution of corrosion depth is not assumed to be constant over time. A similar investigation was conducted by Wang et al. (2021). Their research considered five failure modes: ring deflection failure, leakage failure, burst failure, collapse failure, and bending failure. They found that each of the failure modes exhibited a different probability of failure due to the differences in their failure mechanism and contributing factors causing the failure. Although five failure modes were considered in the study, the addition of other failure stress, such as thermal stress, can increase the robustness of the models.

Moreover, the maximum stress a pipe is subjected to can be determined using finite element modeling (FEM) (Aryai et al., 2020; W. Li et al., 2021). W. Li et al. (2021) developed 243 FEA models to forecast the failure probability based on failure pressure. The reason for developing a large amount of FEA models (i.e., 243) is to fit the stress distribution to an appropriate statistical model. The maximum stress of the 243 FEA models was fitted into four distributions: Weibull, lognormal, normal, and Gumbel distributions. Normal distribution was found most appropriate for the stress distribution and was employed for MCS. Sensitivity analysis was conducted, and thickness was found as the most sensitive parameter, followed by internal pressure and traffic. The study only focused on large diameter pipes. Furthermore, only localized corrosion was considered in the development of the FEA models, while uniform corrosion was ignored.

5.2. Advantages and Limitations of Physical Models

Physical models are based on interpretative equations; therefore, they facilitate a proper understanding of the water pipe failure mechanism. Furthermore, physical models are easy to develop, especially when the model parametrization is simple yet accurate. However, the data required to develop a physical model is costly to get. The data are mainly obtained through site inspection, which is technically difficult to conduct because of the pipes' locations. Furthermore, the collected data may not fully represent the absolute condition of the pipes, as only a segment of the pipe can be practically investigated. For instance, the corrosion depth can vary spatially along the pipe length, which may not be captured by the data collected. Another limitation of physical models is their unsuitability for global applications. This is due to the difference in environmental conditions of various geographical locations.

6. Statistical-Based Models

The second category is the statistical-based models. As the failure mechanism of the pipelines is of complex behavior, the development of statistical-based models does not require a proper understanding of such behavior Unlike physical models, statistical-based models rely on historical data. This type of modeling is suitable for pipes with substantial historical failure data. The summary of the statistically based studies is presented in Table 6. Furthermore, in the case that more than one technique is used in a study, the one with the highest accuracy is reported in the table. In order to choose an appropriate statistical method for fitting historical data to a model, the failure mode of the pipes in the network can be a deciding factor. For instance, the distribution of historical data associated with pipe failure due to corrosion pitting may be different from those associated with pipe deflection. Therefore, the statistical-based models are grouped into parametric and non-parametric models. It should be noted that the statistical-based models explained in this section are the ones found in the literature in our database, other statistical methods such as Gompertz-curve, Bertalanffy, and Kaplan Meier models could be used for fitting the historical data.

6.1. Parametric Models

Parametric models involve a finite number of parameters that describe the historical data under investigation. Parametric models make assumptions regarding the distribution of the data and the form (i.e., linear, exponential, etc.) of the relationship between the variables being studied. This indicates that the shape of the model is fixed and determined by the chosen parameters. Parametric models are relatively easier to interpret since their parameters are known.

6.1.1. Weibull Distribution Models

Different researchers adopted the Weibull distribution model to predict the failure probability of water pipes (Vladeanu & Koo, 2015; Ward et al., 2017). Equation 5 represents the failure probability $F(t)$ of a pipe at time t using the Weibull distribution.

Table 6
Summary of Statistically Based Studies

Authors	Methodology	Validated?	Evaluation metric	The most important factors considered	Type of data	Material type
Al-Ali et al. (2020)	Logistic regression	No	0.74 (Acc)	Diameter, material type	Historical data	Concrete, DI, PVC, FRP, and others
Konstantinou and Stoianov (2020)	Logistic regression and Linear Discriminant Analysis (LDA)	Yes	0.81 (AUC)	Pressure and diameter	Historical data	AC, DI, and CI
Weeraddana et al. (2020)	Gaussian process regression + Bayesian model	Yes	0.73 (AUC)	–	Historical data	AC and PVC
Phan et al. (2019)	Weibull distribution model	No	–	–	Historical data	CI and DI
Tchórzewska-Cieślak et al. (2019)	Bayesian model	No	–	–	Historical data	–
Garcia et al. (2019)	Clustering-based spatiotemporal analysis	No	–	–	Historical data	CI
Ismaeel and Zayed (2018)	FANP and PROMETHEE + probability theory	Yes	94.4 (VF)	Wall thickness, leaks	Historical data + expert's opinion	–
Ward et al. (2017)	Weibull distribution model	Yes	96.0% (R^2)	–	Historical data	PE and others
Chik et al. (2017)	Bayesian simple model	Yes	0.75 (AUC)	–	Historical data	CI
Luo et al. (2017)	Hierarchical beta process	Yes	0.798 (AUC)	–	Historical data	–
Elsawah et al. (2016)	Homogenous Poisson model	No	–	–	Historical data	CI, steel, PVC, DI
Shin et al. (2016)	Bayesian inference + Markov chain Monte Carlo method	No	–	Diameter, length	Historical data	Ductile cast iron
Vladeanu and Koo (2015)	Weibull distribution model	Yes	2.71% (PE)	–	Historical data	AC, CI, DI, concrete, and PVC
Lin et al. (2015)	Hierarchical beta process	Yes	0.827 (AUC)	–	Historical data	–
Z. Li et al. (2013)	Hierarchical beta process	Yes	0.61 (AUC)	–	Historical data	–
Singh and Adachi (2012)	Homogenous Poisson model	No	–	–	Historical data	CI, DI, PVC, concrete
Friedl et al. (2012)	Logistic regression	No	–	Pressure, diameter	Historical data	CI, DI, AC, concrete, PE, PVC, Steel
Karamouz et al. (2012)	Minimum redundancy-maximum relevance + AHP	No	–	Diameter, soil pH, and length	Literature-based data	–
Tchorzewska-Cieslak (2012)	Weighting method	No	–	–	Historical data + expert's opinion	CI, PVC, PE, steel
Kleiner and Rajani (2012)	Bayesian model, ordered list model and logistic regression	Yes	–	Age, length, number of past failures	Historical data	CI, DI, AC
Scheidegger et al. (2013)	Weibull-exponential + Bayesian Inference	Yes	–	Diameter and material	Historical data	DI
Scholten et al., 2014)	Weibull-exponential + Bayesian inference	Yes	–	Diameter and material	Historical data	DI
Singh (2011)	Bayesian model	No	–	–	Historical data	CI, DI, CC, AC, GI, PVC, and others
Debón et al. (2010)	Proportional hazard model	Yes	0.76 (AUC)	–	Historical data	AC, CI, DI, and PE
Carrión et al. (2010)	Proportional hazard model	Yes	–	–	Historical data	CI, PE, and AC
Rogers and Grigg (2007)	Non-homogeneous Poisson distribution model	No	–	–	Historical data	AC, CI, concrete, PVC, steel, and other
Economou et al. (2007)	Non-homogeneous Poisson distribution model + Bayesian model	Yes	17.3% (PE)	–	Historical data	AC

Table 6
Continued

Authors	Methodology	Validated?	Evaluation metric	The most important factors considered	Type of data	Material type
Vanrenterghem-Raven (2007)	Proportional hazard model	Yes	15% (PE)	Age, length, diameter, previous break	Historical data	Steel and non-steel
Mailhot et al. (2000)	Proportional hazard model	No	–	Age	Historical data	–
Cooper et al. (2000)	Logistic regression	No	–	Diameter, soil corrosivity, traffic load	Historical data	CI
Lei and Sægrov (1998)	Weibull distribution model	No	–	–	Historical data	CI, DI, plastic, and others
Andreou et al. (1987)	Proportional hazard model + Poisson model	No	–	–	Historical data	CI, steel, concrete

Note. Acc, percentage of the pipes whose true conditions were predicted correctly; AUC, the area under the curve; VF: validation factor; PE, percentage error.

$$F(t) = 1 - e^{-\left(\frac{t-\gamma}{\eta}\right)^{\beta}} \tag{5}$$

where β, γ, and η are the shape, scale, and location parameters. The parameters can be determined by conducting a regression analysis of the historical failure data.

In the process of developing a risk model for water distribution networks, Phan et al. (2019) employed three-parameter Weibull distribution to model the probability of water pipes failure. The model showed that CI pipes exhibited a 100% probability of failing at 60 years, while that of DI pipes was at 90 years. Thus, CI pipes are more prone to failure. However, limited historical data was used to develop the model; hence, the model shows low accuracy. Vladeanu and Koo (2015) applied two-parameter Weibull distribution to achieve the same objective. The network comprises AC, CI, DI, PVC, and concrete pipes. Due to the unavailability of complete historical data, the authors assumed that the first breakage experienced by each of the pipes happened after 74 years of installation. This assumption may either underestimate or overestimate the network failure probability. Similarly, Ward et al. (2017) applied a 3-parameter Weibull distribution and found that the distribution was suitable for incomplete historical data left-truncated. The model was applied to two case studies. The accuracy of their model was investigated by plotting the predicted failure count against the observed failure count. All the pipe materials had an R^2 greater than 0.96. Although the main output of the model is the failure probability of each pipe material, the failure count was used to identify the pipe age range that experiences most failure.

6.1.2. Poisson Distribution Models

Historical failure data can also be fitted to a Poisson distribution to determine the failure probability of a system. Using the Poisson distribution, the probability of occurrence of an event within a specified interval is given by Equation 6.

$$p(\lambda, n) = \frac{e^{-\lambda} \times \lambda^{n}}{n!} \tag{6}$$

where n is the number of event occurrences, and λ is the mean value (i.e., failure rate) at a specific interval. Therefore, the failure probability of a water pipe can be expressed by Equation 7 (Singh & Adachi, 2012). Based on the failure rate (λ), Poisson distribution can either be homogenous or non-homogeneous.

$$P_f = 1 - \frac{e^{-\lambda} \times \lambda^{0}}{0!} = 1 - \frac{1}{e^{-\lambda}} \tag{7}$$

6.1.2.1. Homogenous Poisson Distribution Models

A Poisson distribution model is classified as homogenous when it has a constant failure rate. In the process of developing a risk model for a municipality in Canada, Elsawah et al. (2016) developed a homogenous Poisson

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model for predicting the failure probability of water pipes. The failure rate was determined based on historical failure data for the last 5 years. The results indicated that galvanized steel pipe exhibited the highest failure probability compared to other pipes, while the failure probability of PVC, CI, and DI are similar. No attempt to validate the model with other historical or field data was made; hence, the model's prediction accuracy may not be generalized. Furthermore, Singh and Adachi (2012) assumed homogenous Poisson distribution to fit the historical data of a water utility in Honolulu, USA. The annual failure rate from 1988 to 2008 was determined from the historical data and employed in the development of the model. Concrete pipes were found to have the lowest average probability of failure, followed by DI pipes. As one would expect, CI has the highest average failure probability. It should be noted that the homogenous Poisson model may be inadequate for failure prediction, as the failure rate of water pipes is not always constant due to the complex mechanism of pipe deterioration.

6.1.2.2. Non-Homogeneous Poisson Distribution Models (NHPP)

The failure rate varies with time in the NHPP. Rogers and Grigg (2007) employed NHPP in predicting the water pipe failure probability of a utility in the USA. However, the NHPP model requires a minimum of three break records for a pipe before it can be applied since the model is governed by the time-varying failure rate, which is an integral function (i.e., two break intervals are needed); else, the governing equation will be unsolvable. Economou et al. (2007) modified the traditional NHPP model to deal with the zero inflation in the historical data of a utility in New Zealand. Excess numbers of zero points characterize the historical failure data. The data comprised 532 AC pipes, where only 81 of them had exhibited one or more failures. Their model suggested allowing for zero inflation in failure prediction increases the predictive capacity of such a model. A major limitation of NHPP models is that they are memoryless, since the effect of previous failure is not taken into consideration while determining the subsequent failure rate.

6.1.3. Proportional Hazard Models (PHM)

While Cox originally developed the PHM for medical applications, it has been applied for pipe deterioration mechanisms; thus, it has been used to predict pipe failure probability (Debón et al., 2010; Mailhot et al., 2000). Generally, the PHM models are used in determining the hazard function of a system. From the hazard function, the reliability of such a system could be determined through its failure probability. The general form of the Cox proportional hazard model is represented by Equation 8.

$$\lambda(t, x_1 \ldots x_p) = \lambda_0(t) \times \exp(\beta_1 x_1 + \ldots + \beta_p x_p) \tag{8}$$

where $\lambda(t, x_1 \ldots x_p)$ is the hazard function, $\lambda_0(t)$ is the baseline hazard function at time "t," which describe the hazard when no covariate is considered. The coefficient of the covariate, x (i.e., explanatory variables) influencing the risk of a system is denoted by β. There are two approaches to develop PHM models: semi-parametric and parametric methods. In the semi-parametric approach, the baseline model is left undefined (non-parametric), which eliminates the bias of assuming the shape of the hazard function. However, an assumption about the beta parameter is made (parametric). This is the case for the Cox PHM model. On the other hand, an assumption about the hazard function and the beta parameter is made in the case of parametric PHM models such as Weibull and exponential PHM models. An interesting fact about PHM models is their ability to estimate the relative importance of explanatory variables on water pipe failure, for example, without knowing the form of the hazard function.

The failure probability of water pipes in a medium-sized water utility company in Spain was modeled by Debón et al. (2010) using the Cox PHM. The pipes in the network have been installed since 1941; however, the failure data from 2000 onwards to the time of the model's development is only available. Due to this, 98% of the data used in the model development was left-censored. Moreover, only the failure year is recorded in the limited data; hence, failure times are assumed. Based on the interpretation of their results, it could be inferred that the hazard rate of shorter pipes is lower compared to longer ones. This shows that a longer pipe has a higher failure probability. Similar trends have been noticed in pipes with higher pressure. However, an inverse relationship between pipe diameter and failure probability was reported. Although the AUC of the model is 0.76, the accuracy may increase if the data quality is improved. Furthermore, with the aim of identifying the most influencing factors on water pipe failure, Vanrenterghem-Raven (2007) employed Weibull and Cox PHM. Right censorship was applied to the pipes since only 6.5% of the pipes had experienced at least one breakage. The Cox PHM was used to identify the most significant factors and their interdependencies, while Weibull PHM was used for failure prediction. The

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results indicated that pipe age, diameter, and previous break are the most significant factors. However, a main disadvantage of the PHM model is that the hazard ratio is constant and does not change over time. This is not true for water pipes, as the deterioration mechanism depends on various factors that are dynamic and time dependent.

6.1.4. Logistic Regression (LR) Models

LR is a regression form used to solve classification problems. In this type of modeling, the historical failure data is categorized into two, where a value of 1 is usually assigned to failed pipes and 0 to none failed pipes. The probability of water pipe failure, for instance, using the LR approach, can be represented by Equation 9.

$$P_f = \frac{1}{1 + e^{-z}} \tag{9}$$

and

$$z = b_o + b_1 X_1 + b_2 X_2 + \ldots b_p X_P \tag{10}$$

where b_o is the intercept of the regression line, X_1–X_P are the explanatory variables and b_1–b_p are their coefficients, respectively.

Al-Ali et al. (2020) employed LR to analyze the failure of 8 different types of pipes. Out of the 43 independent variables used for the predictive model, 16 variables were statistically significant and formed the basis of the regression equation. Although the prediction accuracy of the model is more than 70%, it can be improved if more comprehensive velocity data is used to develop the model, as only 20% of the velocity data was available, while an absolute value was assumed for the rest. Additionally, more explanatory variables such as temperature, bedding factor, and water hammer, amongst others, could be added to make the model more robust.

Furthermore, the logistic model of Cooper et al. (2000) used input parameters such as pipe diameter, soil corrosiveness, the proximity of pipes to each other, traffic load, and urban development year. It should be noted that pipe age was not used in the model, as it is absent in the historical data, contributing to the limitations of the model. Their results indicated that the "proximity of pipes to each other" is a significant variable in failure prediction. This shows that this parameter needs to be explored in further research, as many studies have not paid attention to it.

6.2. Nonparametric Models

Nonparametric models are models whose parameters are infinite and not predefined before the development of the model. Unlike parametric models, no assumption is made regarding the distribution of the data or the functional form of the relationship between the variables. This makes nonparametric models to be more flexible than the parametric ones, but it also indicates that nonparametric models can be relatively difficult to interpret.

6.2.1. Bayesian-Based Models

The Bayesian-based model is a type of statistical model, where the concept of probability is used to deal with uncertainty associated with both the inputs and output of the model. Bayesian models stand on the concept of Bayes' theorem presented in Equation 11.

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)} \tag{11}$$

where the probability of A occurring, given B, is denoted by $P(A|B)$ while the probability of B occurring given A is denoted by $P(B|A)$. $P(A)$ and $P(B)$ are the probability of A and B occurring, which are referred to as the prior and marginal likelihood, respectively. Furthermore, $P(A|B)$ is termed the posterior probability.

Singh (2011) leveraged Bayes' theorem to determine the failure probability of seven pipe types based on various factors causing failures. The factors considered are break cause, pipe age, pipe diameter, and soil type. The first process was to determine the prior probability of pipe failure based on any of the considered factors given its pipe material. The second stage involved the calculation of posterior probability based on the result of the prior probability. The prior probability will allow the utility managers to know the dominant cause of water pipe failure, while the posterior probability will assist the utility managers in deciding the best choice of pipe material for a particular location. It should be noted that this method is suitable for determining the failure probability in the current year of assessment. An attempt to use the model for predicting future failure probability might give inaccurate results unless the database is updated; otherwise, various assumptions will need to be made.

Chik et al. (2017) proposed a Bayesian simple model (BSM) involving four steps for estimating the failure probability. The steps include (a) grouping the pipes based on the number of failures until the year before the assessment year; (b) grouping the pipes based on the number of failures in the assessment year (c) counting the number of pipes in each group; and (d) estimating the failure probability of the pipes in each group based on the assumption that failure probability of water pipes follow Bernoulli distribution. The BSM model was compared with hierarchical beta process (HBP) and the Nonhomogeneous model, which showed comparable accuracy. However, their results found that the BSM model's accuracy for long-term prediction depends on the availability of new data. For instance, if the available data used for training the model is up till 2020, the estimated probability of failure for the same group of pipes will be the same for 2021, 2022, and so on, unless new data is available to update the model. The grouping of pipes referred to in the study by Chik et al. (2017) is a result of unavailability of data relating to the network, which is a typical issue in many WDNs. Three common characteristics of WDN data are right censoring, left truncation, and exclusion of replaced pipe data (Scheidegger et al., 2013). Right censored data are pipes that are yet to experience any failure since installation or last replacement. Data related to pipes that have been installed before failure records are systematically observed are referred to as left-truncated data. Hence, the number and time of failures of these pipes are unknown. The third characteristic refers to the absence of replaced pipe data, which may be because of deleting a replaced pipe record from the database or the pipe replacement was done before establishing a record database.

Furthermore, Tchórzewska-Cieślak et al. (2019) used the Bayesian model to determine water pipes' total and conditional failure probability based on the length of pipe and number of failures. Their investigation includes distribution and transmission pipes. It was found that the failure probability of the distribution water pipes was higher than transmission pipes.

Shin et al. (2016) used a competing hazard model to estimate the failure probability of water pipes in a city in South Korea. The estimation was done using a Bayesian Inference based on Markov Chain Monte Carlo Method. They argued that it is important to investigate the effect of a competing event on a pipe's failure. Hence, pipe failure due to burst in the pipe's body was defined as the main failure event (termed as B-burst), while burst in the connection part of the pipe was defined as the competing event (termed as C-burst). For the pipe material tested (ductile cast iron), the result showed that the pipe exhibits a lower B-burst compared to C-burst.

Furthermore, the failure probability of individual pipe belonging to a certain homogeneous group of pipes was investigated using likelihood ratio obtained via Bayes' theorem (Kleiner & Rajani, 2012). The pipes were grouped based on previous number of failures. The results were compared with those obtained from a LR model and ordered list (a heuristic-based technique) model. In terms of evaluation metric, no model was superior to other as performance of each model was different for various datasets.

6.2.2. Hierarchical Beta Process (HBP) Models

The HBP is a model that is capable of predicting the failure probability of water pipes by regrouping pipes with similar features. It usually consists of three phases, including the beta, the Bernoulli, and the hierarchical processes. The HBP model can be referred to as a non-parametric Bayesian model as the beta and Bernoulli processes can be employed as prior distribution for the hierarchical process. The beta and Bernoulli processes are conjugates of each other.

Luo et al. (2017) analyzed pipe failure using two algorithms based on the Bayesian framework. The first algorithm employed the Infinite Gamma-Poisson Mixture Model, a representation of the Dirichlet process, to assign an index to pipe groups based on similar features. Afterward, the output of the first process was used as input for developing the HBP model. Prior to the development of the HBP model, the beta-Bernoulli process was generated to estimate the prior failure probability of each pipe group, which were subsequently regenerated and ranked using the HBP model. The prediction accuracy of the proposed model increased by more than 10% compared to the conventional HBP model that uses knowledge of domain experts rather than the Infinite Gamma-Poisson Mixture Model for pipe grouping. However, the proposed model could be more realistic by considering factors related to the weather (e.g., temperature) and operation (e.g., internal pressure) of the network.

Similarly, the model updating capability of the nonparametric Bayesian method was explored by Lin et al. (2015) for the failure probability prediction. Like the study of Luo et al. (2017), two processes were involved in the

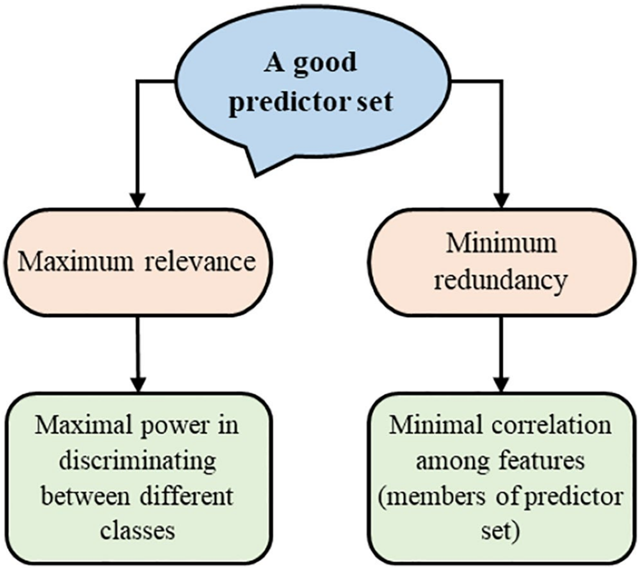


Figure 8. Specifications of a good predictor set.

development of the model. However, the first process used the Chinese restaurant process (CRP) for generating the group index. As CRP is employed as a representation of the Dirichlet process, it mimics the influx of customers (i.e., data points) into a restaurant and getting assigned to different tables (i.e., clusters). The second process of developing the HBP model follows the same methodology as that of the study by Luo et al. (2017). It should be noted that more influencing factors affecting the failure probability are considered in the study of Lin et al. (2015) compared to that of Luo et al. (2017). These factors include soil expansiveness, soil map, soil geology, availability of coating, and distance to a traffic intersection. Additionally, the model developed by Lin et al. (2015) had higher prediction accuracy compared to that of Luo et al. (2017), probably because more influencing factors were considered in the former.

6.3. Other Statistical-Related Models

In addition to the probability theory, Ismaeel and Zayed (2018) employed multicriteria decision methods such as fuzzy analytical network process, preference ranking organization method for enrichment evaluation, multi-attribute utility theory for calculating performance indices for both water pipes and their associated accessories such as valves. The failure probability of each component was determined from the performance index. The model was built on expert opinions, which was subsequently validated by applying it to a case study. On average, the model achieved a prediction accuracy of 94.4%, using the validation factor proposed by Zayed and Halpin (2004). Similarly, Karamouz et al. (2012) developed an algorithm to determine the vulnerability of water pipes. Their definition of vulnerability centers on the failure probability of water pipes. Out of six factors determined through literature review, three influencing factors relating to water pipe failure were selected as the most representative factors by Minimum Redundancy-Maximum Relevance (MRMR) feature selection method, shown in Figure 8. Subsequently, Analytical Hierarchical Process (AHP) was used to give weights to these three factors. Finally, the probability of any pipe failing in a distribution network was estimated from the aggregation of the AHP results and the values of each factor determined from the MRMR. However, the developed model was applied to a hypothetical case study, which raised a question on the real-word applicability of such a model in addition to the fact that the determination of weights for the factors are subjective.

Moreover, Tchorzewska-Cieslak (2012) estimated the failure probability of water pipes by making some assumptions based on the failure rate (number of failures/km/year). They assumed low, medium, and large failure probability when the failure rate is less than 0.5, equals to 0.5, and greater than 1, respectively (i.e., weighting method). This assumption is subjective and may not be applicable to other WDNs.

6.4. Advantages and Limitations of Statistical-Based Models

Since statistical-based models can be built on historical failure data of water pipes from installation until the out-of-service time these models could be handy in modeling the entire life cycle of water pipes. Another benefit of this model category is that it is cost-effective. However, the prediction accuracy of statistical models depends on the historical data quantity and quality. For instance, Bayesian models need to be updated continuously with the required data in order to sustain their prediction accuracy. Additionally, a limited number of variables, mostly due to lack of data, are included in the development of statistical-based models, which can result in inappropriate predictions. Furthermore, statistical-based models require formulating some assumptions for model development, which may need some level of expertise in addition to their computational complexity.

7. Machine Learning-Based Models

In the past few decades, ML-based models have emerged as the way forward in modeling water pipe failure due to their robust predictive capacity. ML models are developed by simulating human intelligence on computer systems (Samoili et al., 2020). In this section, models relating to fuzzy and ML algorithms are reviewed and presented in Table 7.

Table 7
Summary of Machine Learning-Based Studies

Authors	Methodology	Validated?	Evaluation metric	The most important factors considered	Type of data	Material type
Fan et al. (2022)	LightGBM, LR, SVM, ANN, k-NN	Yes	(0.81) AUC	Interval to last break, cold days, hot days, pipe length, pipe age	Historical data	CI, DI, and others
Chen et al. (2022)	RF, boosting trees, XGBoost	Yes	0.899 (AUC)	–	Historical data	CI, DI, PVC, and others
Rifaai et al. (2022)	LR	Yes	0.680 (AUC)	Years from past failure, length, number of past failure	Historical data	AC, CI, DI, PVC, and others
Raspati et al. (2022)	RF	Yes	–	Age, length, internal pressure, and pipe material	Historical data	AC, CI, DI, GRP, PE, and PVC
Weeraddana et al. (2021)	Random survival forest	Yes	0.719 (AUC)	–	Historical data	AC, CI, DI, PVC, PE
Jara-arriagada and Stoianov (2021)	LR	Yes	0.814 (AUC)	Pressure	Historical data	AC, CI, PE
Giraldo-González and Rodríguez (2020)	GBT, SVM, ANN and Bayes	Yes	0.998 (AUC)	Previous failure, length, precipitation	Historical data	AC and PVC
Rahbaralam et al. (2020)	LR and XGBoost	Yes	0.859 (AUC)	Age, material, length	Historical data	DI, PE, steel
Kumar et al. (2018)	Gradient boosting decision trees	Yes	0.62 (Precision)	Previous failure, age, diameter	Historical data	CI, DI, and others
Konstantinou and Stoianov (2020)	Gradient boosting, ANN, RF	Yes	1.0 (AUC)	Age, length, internal pressure	Historical data	AC, DI, and CI
Al-Zahrani et al. (2016)	Fuzzy-based	No	–	–	Historical + literature data	AC, PVC, steel
Francisque et al. (2009)	Fuzzy-based	No	–	Free chlorine and number of previous breaks	Historical data + experts' opinion	CI, DI, steel, and others
Salehi et al. (2021)	Fuzzy-based	No	–	–	Historical data + literature data	CI, DI

Note. AUC, the area under the curve.

7.1. Fuzzy-Based Models

Fuzzy-based models are used to tackle complexity, vagueness, and uncertainty in different systems. In the case of water pipes, the failure mechanism is complex and not properly understood since different factors interact ambiguously to cause the pipe failure. Hence, fuzzy-based models can be employed to solve this problem. In the fuzzy approach, a crisp, imprecise variable is fuzzified using defined membership functions. Afterward, a set of fuzzy rules is applied to the fuzzified variable to modify it. Subsequently, the fuzzified variables are defuzzified to get an unbiased crisp variable.

Al-Zahrani et al. (2016) developed a fuzzy-based model that uses 13 input factors relating to the structural integrity of the pipes, water quality, and operation of the network. These factors were arranged in a hierarchy, and fuzzy membership functions were defined for each of the factors based on the characteristics of each factor obtained in the literature (AWWA, 2002; Sarbatly & Krishnaiah, 2007). Subsequently, AHP was employed to determine the relative weights of each fuzzy set. After aggregating the fuzzy sets and AHP, the fuzzy variables were defuzzified to determine the failure probability based on the historical data. Although this approach quickly estimates the failure probability, high precision may not be achieved as it was used as an approximate method. Moreover, it is not clear how the authors assumed some values for the weight of the fuzzy sets.

In a related study, fuzzy rule based, and fuzzy-synthetic evaluation were employed for prioritizing water pipes based on their risk index. The risk index is a multiplication of failure probability and consequences of water pipes. Similar to the approach employed by Al-Zahrani et al. (2016), the failure probability index for each water pipe was determined by aggregating the fuzzy sets with the weights of each factor obtained from the AHP analysis.

Afterward, the risk indices were developed, and the most probable pipes to fail were visualized using the GIS map. The model did not capture critical influencing factors of water pipe failure, such as pipe diameter and internal pressure. The ability of fuzzy-based models to be built on imprecise, distorted, and vague data is a major advantage over other techniques. However, a major limitation is its reliance on expert knowledge to formulate fuzzy rules.

7.2. Machine Learning-Based Models

ML models can learn or recognize specific patterns from a set of data. ML-based models make future predictions based on the learned patterns when new data are fed into them. It should be noted that some statistical models such as Bayesian Network, LR, Naïve Bayes and so on are adapted as an ML technique to overcome the challenge of computational intensiveness and inability to handle high dimensional data of statistical models. Therefore, some statistical models that are used as an ML method appear in this section. ML models can be broadly classified into supervised, unsupervised, and reinforcement learning models (Abdi, 2016). The input and output variables are clearly defined in supervised learning. In contrast, the machine is left to discover the input and output variables on its own from the data in the case of unsupervised learning. In reinforcement learning, the machine learns from its own experience by using a feedback approach. In this study, only supervised-based models relating to the failure probability of water pipes are reviewed since no studies are found on the other two classes of ML. These models include artificial neural network (ANN), support vector machine (SVM), k-nearest neighbors (k-NN), gradient boosting-based tree (GBT), extreme gradient boosting (XGBoost), and random forest (RF). k-NN can be used as supervised or unsupervised ML algorithm, however, it has been used as supervised learning algorithm in the studies reviewed in this paper. It should be noted that these algorithms can be used to solve regression and classification problems (Abdelmageed et al., 2022). However, the reviewed studies have approached the failure probability of water pipes as a classification problem using historical data.

Fan et al. (2022) used five ML algorithms to classify each pipe in a network as either broken or intact. These ML algorithms are lightGBM, ANN, k-NN, SVM, and LR. The five models produced output for each pipe which ranged from 0 to 1, denoting the failure probability of a pipe. 13 factors were considered in the modeling, including 11 continuous variables, while the remaining two variables are categorical. While most of the considered factors are correlated with each other's and with the failure of water pipes, none of them was dominant. This strengthens the hypothesis that the failure of water pipes is a complex mechanism and does not depend on a single factor. Based on the performance indicators such as the prediction accuracy and computational efficiency, the lightGBM algorithm was selected as the best model, followed by the ANN model. An ML interpreter, Shapley Additive exPlanations (SHAP), was adopted to investigate the relative importance of each factor. “Interval to the last break,” “Cold days,” “Pipe length,” “Hot days,” and “Pipe age” were found as the topmost important factors for pipe failure prediction.

Moreover, Rifaai et al. (2022) employed LR to predict the failure probability and mean time to failure of water pipes located in a WDN in Austin, USA. The data set included 244,830 pipes, which are made of AC, CI, DI, PVC, and others. Their model achieved an accuracy of 80%, AUC of 0.69, and Mathew Coefficient Correlation (MCC) of 0.53. However, the accuracy of the model could be improved by selecting the best hyperparameters that could fit the data well and performing feature (i.e., variable) selection prior to the modeling.

In order to solve the problem of limited historical failure data experienced in some water utilities, Chen et al. (2022) combined historical data of six utilities to make failure probability predictions. Three algorithms were used: RF, GBT, and XGBoost. For each of the six utilities, four datasets were prepared. The first data set consists of half-historical data of a reference utility, while the second data set represents the full historical data of such utility. The third data set, which is a union of all the utilities' historical data, was prepared in such a way that the pipe material distribution of each of the utilities matched one another. Meanwhile, the fourth data set is a union of all the utilities' historical data without considering their material distribution consistency. Their results indicated that using data from other utilities for failure probability prediction of a reference utility does not improve the prediction accuracy of such a model. Additionally, for the first and second datasets, the prediction accuracy of pipe failure is not associated with the quantity of the data but rather the quality of the explanatory variables. Overall, RF had the highest prediction accuracy. Similarly, although not absolutely enough, the study of Raspati et al. (2022) that used RF for failure prediction noted that an advantage of RF over other “black box” ML algorithms is its interpretability and simplicity. The interpretability here means RF models could be visualized, and the relationship between the explanatory variables with respect to the prediction could be seen.

Furthermore, GBT, SVM, ANN, and Bayes were employed to predict the failure probability of water pipes (Giraldo-González & Rodríguez, 2020). The models incorporated 11 input variables. The performance of the algorithms was assessed using the prediction accuracy formula (Equation 12), recall value on the confusion matrix, and AUC of receiver operating characteristic. It was observed that the accuracy metric does not give reliable performance evaluations since the data consists of non-failed pipes than the failed ones (i.e., imbalanced data). Hence, the classifiers, especially ANN, were majorly able to predict non-failed pipes correctly. Therefore, it is better to assess the performance of ML classifier-based models using the cofunction matrix and AUC. Overall, GBT and SVM achieved the best performance in terms of failure prediction.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})} \tag{12}$$

where TP (true positive) and TN (true negative) represent the number of correctly classified pipes as failed and non-failed, respectively. On the other hand, FP and FN represent the number of pipes that are wrongly classified as failed and none-failed, respectively.

7.3. Advantages and Limitations of ML-Based Models

As an important benefit, many ML-based models (i.e., non-parametric) do not require pre-assumptions on the distribution and form of pipe's failure data. Furthermore, ML-based models are able to handle heavy data sets effectively within a limited time. Moreover, the introduction of automated ML tools such as TPOT, Orange, and RapidMiner, amongst others, has made ML applications easier and accessible to individuals who are not experts in programming languages (Baharun et al., 2022; Demšar & Zupan, 2013; Randal et al., 2016). However, ML-based models are as good as the quality and quantity of the data used in developing them. Hence, low quality and limited data will result in inaccurate predictions. Besides, ML models developed with limited data and an algorithm that optimizes its parameters may lead to overfitting (Chen et al., 2022). Hence, such a model cannot be generally applied to other historical failure data. Since ML-based models require a substantial amount of data, this implies that the models are most suitable for pipes that exhibit higher failure frequency. Additionally, some of the ML algorithms have zero to low interpretability, which might be difficult to understand the relationship between the explanatory variables and the output of such models.

8. Failure Probability Integration

The three methods discussed above can be used to estimate the failure probability of individual pipes due to a particular mode or cause of failure. However, different failure probabilities can be combined together to give a robust failure probability of a pipe or network. Hence, this section discusses methods that have been used to combine failure probabilities of water pipes. Summary of the previous studies relating to failure probability integration is presented in Table 8. While fault tree analysis and copula functions are presented in this section based on the retrieved previous papers, it should be noted that Bayesian Networks and event trees can also be adopted for failure probability integration.

8.1. Fault Tree Analysis (FTA)

FTA is a type of analysis that shows the relationship between the failure of a system (i.e., the top event) and its associated causes (i.e., intermediate, and basic events). These events are connected by logic gates. “OR” and “AND” are the most used logic gates (Kim et al., 2021). If a sub-system (i.e., events) is defined using the “OR gate,” this means that the failure of any component will cause the failure of such sub-system. On the other hand, a sub-system defined by the “AND gate” implies that the system will continue to function as long as one of its components has not failed. For instance, a pipe may fail either due to due to mechanical damage or accumulated stress from corrosion. These two events would be connected with an “OR gate.” Table 9 shows the diagrammatic representation of FTA symbols and their interpretation. Additionally, the failure probability of a pipe can be estimated by integrating failure probability from multiple failure modes in the assessment.

The risk of WDN in a city was investigated using FTA. The network was divided into 11 parts and the risk of water suspension in each part was estimated using FTA. The failure probability of each pipe was estimated using

Table 8
Summary of Studies Relating to Failure Probability Integration

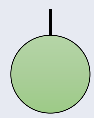
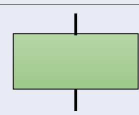
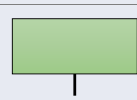
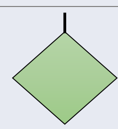
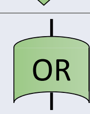
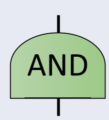
Authors	Methodology	Validated?	The most important factors considered	Type of data	Material type
Huang et al. (2023)	Copula functions + finite element method	No	–	Historical + simulation data	CI and PVC
Kim et al. (2021)	Fault tree analysis + logistic regression	No	–	Historical data	Steel and ductile cast iron
Phan et al. (2018)	Fault tree analysis + limit state approach	No	Wall thickness, loads, corrosion size	Idealized and literature-based data	–
Lindhe et al. (2012)	Fault tree analysis + Markov process	No	–	Historical data + experts' opinion	–
Tchorzewska-Cieslak and Boryczko (2010)	Fault tree analysis	No	Pipe material, pressure, and corrosion	Historical data	CI, steel, and plastic
Lindhe et al. (2009)	Fault tree analysis + Markov process	No	–	Historical data + experts' opinion	–

a LR model and the total failure probability of each part of the network was determined by defining logic gates between the events. Similar approach was followed in the study by Lindhe et al. (2009). As FTA is a deductive process of a system failure, event tree analysis (ETA) is an inductive process capable of showing all possible consequences or outcome resulting from a system failure (i.e., pipe failure). However, limited articles are available on ETA of water pipe failure.

8.2. Copula Functions

Probability state space is usually between 0 and 1. Joining two marginal probabilities of different distributions, events, modes, or scenarios may not directly fit in the probability space. Therefore, Copulas are employed to

Table 9
Fault Tress Analysis Symbols and Interpretation

Event symbols and logic gates		Interpretation
Basic event		This depicts an event that cannot be developed further (i.e., the event at the bottom).
Intermediate event		It represents a fault event that is between basic and top events.
Top event		This is the event that its causes are being investigated.
Undeveloped event		It represents an event that cannot be developed further due unavailability of sufficient information regarding it.
OR gate		This indicates that the output event will occur when at least one of its input components occur.
AND gate		This indicates that the output event will only occur when all the components of its input occur.

generate joint distributions based on a particular form of a copula function. Copula functions can be classified under three families: elliptical (i.e., Gaussian), Archimedean (i.e., Gumbel), and vine copulas. Furthermore, copula function is capable of measuring the associated interdependencies between random variables (Atique & Attoh-Okine, 2016).

Huang et al. (2023) studied the failure probability of a network located in Suzhou city in China using Copula function technology. The fragility (conditional failure probability) of each component of the network was investigated in terms of transient ground displacements and permanent ground deformation. A LSF was established for each component of the network and 10,000 MC simulations was conducted to estimate the failure probability of each component. Subsequently, Copula functions such as Gauss, Clayton, Gumbel, and Frank were used for the estimation of failure probability of the network. The results generated from the Copula functions show a higher safety reserve for WDN design compared to the result of finite element method.

9. Frequency-Based Analysis of the Influencing Factors and Material Types

This section presents a brief discussion about the frequency analysis of the factors that influence the failure of water pipes, which are resultantly used in developing the prediction models and material types used in prior investigations. Table 10 reports the descriptive statistics for these factors, whereas Figure 9 displays the associated normalized percentage of pipe material. The frequency is determined by the number of studies that have employed each influencing factor to model the probability of water pipe failure. This type of analysis enables determination of the factors that have been understudied.

It can be seen from Table 8 that the predictors can be categorized into four classes: physical and pipe-related, environment-related, operation-related, and social-related predictors. In terms of frequency, the three top predictors are “pipe diameter,” “pipe age,” and “internal pressure.” It could be inferred that these predictors have a significant impact in modeling water pipe failure probability, as they have been included in the majority of studies. On the other hand, “population,” “percentage without health insurance,” “poverty percentage,” “groundwater condition,” “water age,” and “water temperature” are the predictors with the least frequency. This could indicate that these predictors are either insignificant in developing the predictive models, or they are understudied. In order to determine the relative importance of the predictors based on their category level, the frequency has been normalized. Findings indicated that the physical & pipe-related and environment-related predictors are the most adopted variables for developing water pipe failure probability models, while social and operation-related are the least explored predictors. Hence, more investigations are needed to determine their importance.

Figure 9 shows that the most used pipe materials are cast iron and ductile iron, whereas galvanized iron and glass-reinforced plastic are the least used materials. According to these results, even though CI pipes are no longer manufactured in many countries, they nevertheless account for the majority of pipes in service for most water utilities. This supports the findings of Wilson et al. (2015), who revealed that CI pipes account for 28% of water pipelines in both Canada and the USA. Furthermore, the deterioration rate, environmental impact and the advancement in material technology affect the choice of pipe material for WDN. For instance, the use of AC pipes in Hong Kong's WDN has been discontinued since 1986 due to its environmental impacts and brittleness in withstanding external stress (Water Supplies Department HKSAR, 2009). In addition, AC pipe material has been banned in more than 52 countries as they are proven to cause different types of cancers (Ladou et al., 2010).

10. Gaps and Future Directions

Based on the comprehensive and holistic review carried out in this study, existing gaps have been identified in the literature, and recommendations to address these gaps are discussed in this section. Figure 10 summarizes the identified gaps and future directions.

10.1. Adoption of Machine Learning Models for Predicting the Failure Probability of Water Pipes

Out of the reviewed 76 papers in this study, only 18.05% adopted ML models for predicting the failure probability, indicating that the capability and robustness of ML models need to be further explored. More importantly, none of these studies used any form of unsupervised learning models for the failure probability prediction. Some of the advantages of unsupervised learning approaches include (a) the ability to recognize patterns within

Table 10
Descriptive Statistics of the Influencing Factors

Category	Predictors	Frequency	Normalized frequency
Physical and pipe related	Age	26	0.546
	Burial depth	4	
	Coating	2	
	Crack depth	4	
	Diameter	35	
	Length	22	
	Material type	27	
	Number of hydrants	2	
	Number of valves	2	
	Elastic modulus	8	
	Thickness	14	
Total		146	
Environment-related	Bedding condition	2	0.288
	Cold days	2	
	Corrosion depth	3	
	Corrosion length	2	
	Surface load	3	
	Frost load	4	
	Groundwater condition	1	
	Hot days	2	
	Land use	2	
	Precipitation	2	
	Soil corrosivity	13	
	Soil elastic modulus	5	
	Soil type	6	
	Temperature	9	
	Traffic load	13	
	Unit weight of soil	8	
Total		77	
Operation-related	Internal pressure	25	0.161
	Number of previous breaks	12	
	Water age	1	
	Water pH	2	
	Water temperature	1	
	Water velocity	2	
Total		43	
Social-related	Population	1	0.003
Total		1	
Grand total		267	

unlabeled data, (b) time-saving capability as there is no need for human involvement, and (c) the ability to understand what humans cannot decode. Furthermore, the predictive capacity of deep learning algorithms needs to be explored. Besides, many ML algorithms are considered "black boxes" because of their poor interpretability. That is, the relative importance of the input variables and their relationship to output variables is rarely explainable.

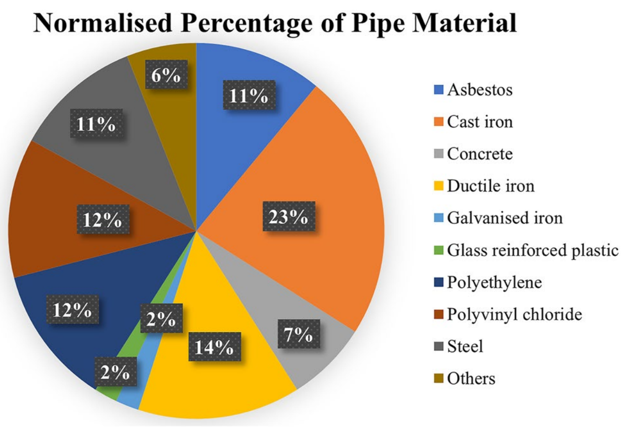


Figure 9. Normalized percentage of pipe material.

Therefore, further research should integrate interpretive algorithms with ML to mitigate this challenge.

10.2. Detailed Models for Modeling Corrosion

Many studies assumed a constant corrosion rate while developing a failure model. In many cases, this assumption is incorrect, resulting in inaccurate predictions. The constant corrosion rate may either overestimate or underestimate the failure probability, which is not economical for the former case. This is because pipes with actual low failure probability may be predicted to have a higher probability of failure, resulting in replacing/repairing actions earlier than required. Corrosion impact on pipelines is a stochastic process; hence, future corrosion models used as part of estimating the failure probability should be modeled as non-linear/stochastic rather than assuming a constant corrosion rate. Moreover, most of the existing models integrating corrosion models into failure prediction assumed that failure occurs due to a single corrosion pit formation. Future research needs to focus on the impact of corrosion pit's colony that may grow with time, as well as their cumulative effect on the structural integrity of such pipes.

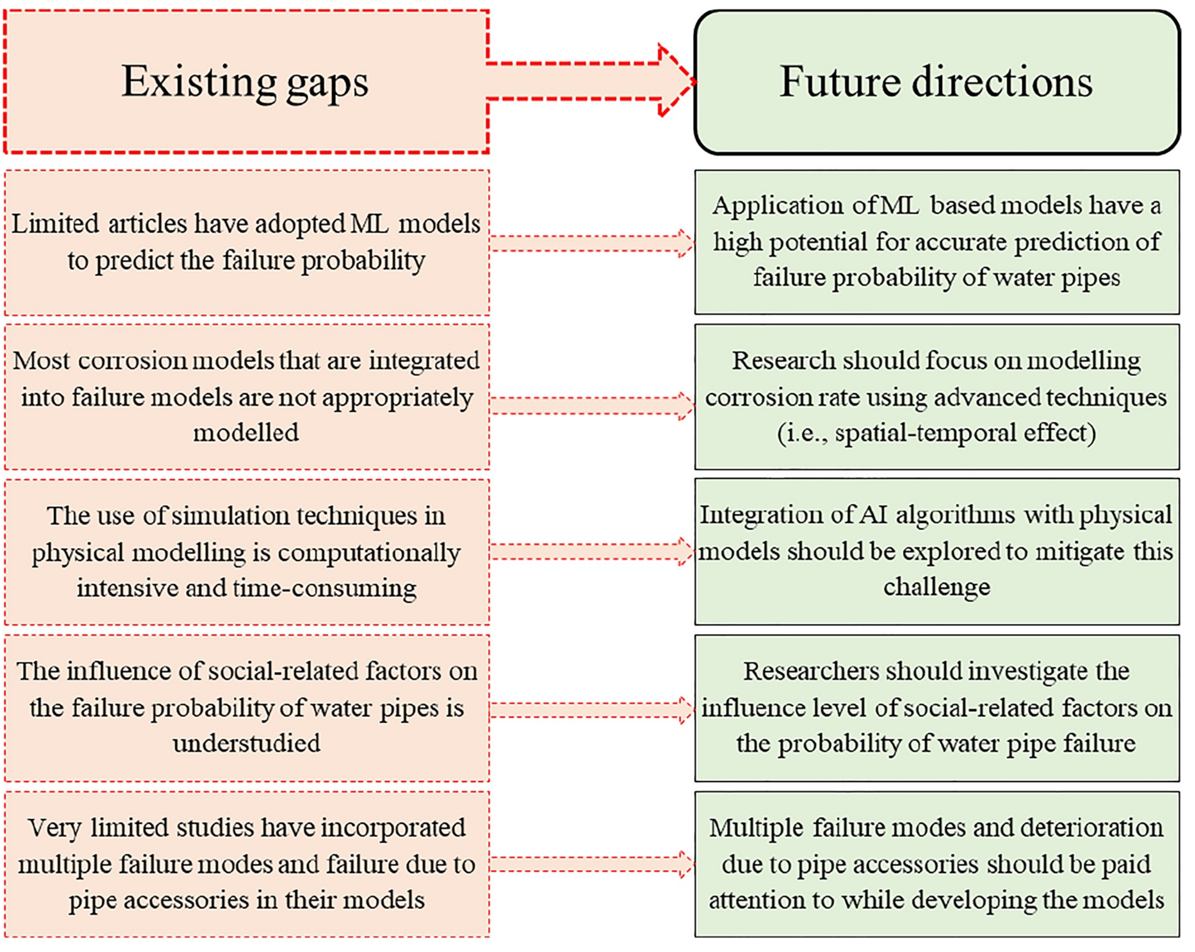


Figure 10. Summary of identified gaps and future directions.

10.3. Establishing Surrogate Models Using Machine Learning

As indicated earlier, the limit state approach is combined with a simulation or analytical technique to determine the failure probability of a pipe. However, the simulation and analytical techniques have some drawbacks, such as computational intensiveness and time-consuming. Future research can develop surrogate models by integrating physical models with ML algorithms to mitigate this challenge. For instance, instead of generating 10,000 MC simulations, 2,000 simulations can be generated and serve as the input data for developing ML-based models.

10.4. Consideration of Social-Related Factors

Social-related factors such as population density are yet to be fully explored. It is essential to explore the effect of these factors in future studies so as to conceptually and numerically understand their impact on the failure probability of water pipes. For instance, it has been demonstrated that areas with high population density exhibited higher failure probability. As a results, it is clear that these and other social-related factors have an impact of the failure probability, which needs to be further explored.

10.5. Consideration of Multiple Failure Modes and Pipe Accessories

Developing an accurate physical model requires a proper understanding of water pipe failure mechanisms. In view of this, very limited studies have considered multiple failure modes. In practice, the probability of a pipe failing due to a single failure mode is low. Hence, due to the complex nature of water pipe failure, multiple failure modes should be considered during the model development. Similarly, research should focus on determining the influence of pipe accessories on its failure probability.

11. Conclusion

It is essential to develop accurate predictive models for estimating the failure probability of water pipes since an unexpected failure leads to enormous water loss, environmental damage, negative impacts on human health, and other undesired consequences. In this regard, this study conducts a comprehensive and holistic review of scholarly literature existing in the domain of failure probability of water pipes. Unlike previous studies, this research adopts a mixed methodology by combining bibliometric analysis with systematic review to avoid the limitation of using either of the approaches. The bibliometric analysis consists of the annual publication trends, keyword co-occurrence analysis, and contribution of the research outlets and influential institutions. The publication trends show that modeling the failure probability of water pipes is gaining momentum as the number of publications increased from one decade to another. Furthermore, the keyword analysis indicates that the application of “ML” in this domain is minimal, thereby suggesting further exploration of these techniques. In terms of journals' contributions, the highest productive research outlet has been identified as “Reliability Engineering and System Safety.” Moreover, three Canadian institutions were indicated to be the most influential organizations.

The systematic review divides water pipe failure probability modeling into physical, statistical, and ML-based models. It was found that physical models are costly though they are easy to interpret. On the other hand, statistical and ML-based models are cost-effective though their accuracy depends on the quantity and quality of the historical failure data. Additionally, a summary table for each of the categories is presented. Using these tables, it is easy to visualize the modeling technique adopted in each previous study, identify the validation status of the models with their accuracy level, know the most important factors employed to develop the models, the type of data used, and the material type. Besides, a frequency-based analysis of the influencing factors was conducted, and it shows that social-related and operation-related factors are understudied. Conclusively, this study provides insightful future research directions based on the identified gaps in the scholarly literature.

Nomenclature

AC	asbestos
CI	cast iron
DI	ductile iron
PVC	polyvinyl chloride

PE	polyethylene
FORM	First Order Reliability Method
FOSM	First Order Second Moment
LSF	limit state function
MCS	Monte Carlo simulation
WDNs	water distribution networks
P_e	soil load (kPa)
P_s	surface load (kPa)
D	pipe diameter (mm)
t	pipe wall thickness (mm)
$d(T)$	time-dependent depth of the defect
A	pipe age
T_{cr}	critical wall thrust (MPa)
σ_m	maximum bending stress (kPa)
σ_y	yield stress (kPa)
σ_b	bending stress (kPa)
l_d	length of corrosion defect (mm)
d_d	depth of corrosion defect (mm)
p_f	failure pressure (kPa)
σ_f	tensile strength (kPa)
σ_o	initial tensile strength (kPa)
δ	maximum corrosion rate
b_o	initial pipe wall thickness (mm)
σ_{uts}	ultimate tensile strength
v_d	radial corrosion rate (mm a^{-1})
v_l	axial corrosion rate (mm a^{-1})
c_d	cold days (days)
h_d	hot days (days)
I_l	interval to last break (years)
L	pipe length
T_a	allowable wall thrust (MPa)
ΔX	ring deflection (mm)

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

No external data was used.

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