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# Progress in Drainage Pipeline Condition Assessment and Deterioration Prediction Models

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**Abstract:** The condition of drainage pipes greatly affects the urban environment and human health. However, it is difficult to carry out economical and efficient pipeline investigation and evaluation due to the location and structure of drainage pipes. Herein, the four most-commonly used drainage pipeline evaluation standards have been synthesized and analyzed to summarize the deterioration and breakage patterns of drainage pipes. The common pipe breakage patterns are also summarized by integrating the literature and engineering experience. To systematically describe the condition of drainage pipes, a system of influencing factors for the condition of pipes, including physical, environmental, and operational factors, has been established, and the mechanism of action of each influencing factor has been summarized. Physical, statistical, and AI models and their corresponding representative models have been categorized, and the research progress of current mainstream drainage-pipe deterioration and breakage prediction models are reviewed in terms of their principles and progress in their application.

**Keywords:** pipeline condition assessment; pipeline deterioration and breakage; influencing factors; artificial intelligence model; machine learning

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## 1. Introduction

Sewage overflow and groundwater leakage have seriously affected urban aesthetics and environmental hygiene [1,2], and the accompanying fetid water bodies [3] and heavy-metal pollution [4] have gradually become focal issues that endanger human health and hinder urban development. At the same time, the operation and maintenance of drainage pipes remain a difficult problem to overcome for the research and engineering community because of their deep burial, complex branching structure, and the large variation in the shape of pipe openings [5,6].

The rapid development of science and technology over the past two hundred years has promoted the construction of urban underground pipelines, and a large number of engineering practices have catalyzed the social demand for pipeline construction, operation, and maintenance [7]. The Water Resources Research Centre (WRc) in the UK pioneered the Manual of Sewer Condition Classification in 1980 [8], which has now been updated to the fifth edition MSCC5 (WRc2013). The manual innovatively classifies pipeline defects into four main categories: structural defects, functional defects, construction defects, and special defects, which has prompted the creation of a Europe-wide standard, which has allowed the different codes to use a common language [9]. On this basis, most European countries have developed and improved the original codes according to their actual engineering status as well as national urban planning and geographical characteristics [10,11]. North America has been slightly behind Europe in developing standard codes for pipeline classification, among which the Pipeline Assessment Certification Program (PACP), established by the National Association of Sewer Service Companies (NASSCO), and the Guidelines for

Condition Assessment and Rehabilitation, published by the National Research Council of Canada, are widely used for large sewers.

At the beginning of the 21st century, the US Environmental Protection Agency (EPA) proposed a new drainage pipeline health condition assessment, which involves the collecting of pipeline data and background information by direct or indirect means and making judgments and predictions on the current or future structural, water quality, and hydraulic conditions of the pipeline through data analysis [12]. At the present time, the construction of a complete pipeline database and the establishment of a scientific and efficient deterioration and breakage prediction model are the core principles of pipeline condition evaluation and operations and maintenance (O&M) management, which have achieved good results in engineering applications [13–15]. However, due to the large temporal and spatial variability of drainage pipeline construction, operation, and maintenance specification standards, and the relatively vague criteria for identifying and selecting influencing factors, pipeline deterioration and breakage prediction models vary greatly in their form [16–18]. Therefore, factors influencing the state of health of drainage pipelines and deterioration and breakage prediction models deserve in-depth research.

In this paper, we have: (a) classified the common drainage pipe damage patterns by combining the standards and engineering experiences of four typical countries; (b) summarized the factors influencing the condition of drainage pipes and the complex mechanism of each factor; (c) sorted the drainage pipe deterioration and damage prediction models into three types: physical models, statistical models, and artificial intelligence (AI) models; and (d) analyzed the various types of representative prediction models and typical applications.

## 2. Drainage Pipe Condition Assessment and Deterioration Patterns

Mohammadi et al. determined the frequency of occurrence of specification criteria or evaluation methods corresponding to relevant results published between 2001 and 2019 by analyzing meta-index data on drainage pipe deterioration breakage prediction models in databases such as ProQuest, and then scaled the data as shown in Figure 1 [18]. Next, we will focus on these specification standards and some other typical standards.

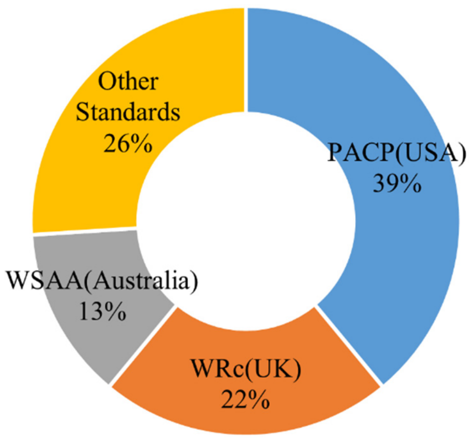



**Figure 1.** Frequency of condition-rating standards in results published between 2001 and 2019 [18].

### *2.1. Pipeline Assessment Certification Manual (PACP)*

PACA is one of typical pipeline standards from North America, which is used for pipeline defect identification and assessment to identify the pipe condition and management. The first version of PACP was developed by National Association of Sewer Service Companies (NASSCO) in 2001. Referred to in the UK Water Research Center (WRc) "Sewer Rehabilitation Manual", the goal of PACP is to identify, plan, optimize, manage, and innovate sewer management systems wherever possible [19].

PACP has a special classification method that contains five types of classification patterns: (1) continuous defects, (2) structural defects, (3) operational and maintenance,

(4) construction features, and (5) miscellaneous features coding. PACP classifies pipeline defects into structural defects and operation and maintenance (O&M), and defects are classified by types into Crack, Fracture, Collapse, Weld Failure, Infiltration, Deposits Attached, and Obstacles [20]. Based on CCTV inspections and operator judgement, defects can be classified by severity into five classes:

5—Defects requiring immediate attention
4—Defects are going to become grade 5 without operation and maintenance
3—Moderate defects will remain deteriorating
2—Defects have not yet begun to deteriorate
1—Pipelines have minor defects

### *2.2. Sewer Rehabilitation Manual (SRM)*

The first edition of SRM can be traced back to 1983, which is the result of the WRc in the United Kingdom starting a five-year research project to develop a method to assess the condition of sewer pipelines [21]. In many ways, SRM and PACP have a lot of similarities; for example, they all have the same classification, and they all have the same grades. A slight difference is that SRM classifies defects into Joint Opening, Crack, Fracture, Deformation, Hole, Broken Pipe, and Collapsed Pipe in concrete pipes [22].

### *2.3. Australian Conduit Condition Evaluation Manual (ACCEM)*

The ACCEM was produced by Sydney Water in 1991 with the aim of addressing the growing problem of pipeline deterioration. Unlike SRM and PACP, ACCEM uses a grade of 1 to 3 to judge the impact of pipeline defects in the first version, but changed to a grade of 1 to 5 in the later versions. Meanwhile, ACCEM classifies pipeline defects into structural defects and hydraulic defects, and it is also different from PACP and SRM [23].

### *2.4. Other Typical Standard*

We have selected China's "Technical Regulations for Inspection and Assessment of Urban Drainage Pipelines" (CJJ181-2012) to complement the standards because it is widely used and well developed. CJJ181-2012 has absorbed the advantages of PACP, SRM, and ACCEM and refined the classification of defects. Some less frequent defects (e.g., Stump Walls and Roots and Scum and Floating Mud) can be found in the CJJ181-2012, and we use these descriptions to refine the pipeline defect summary.

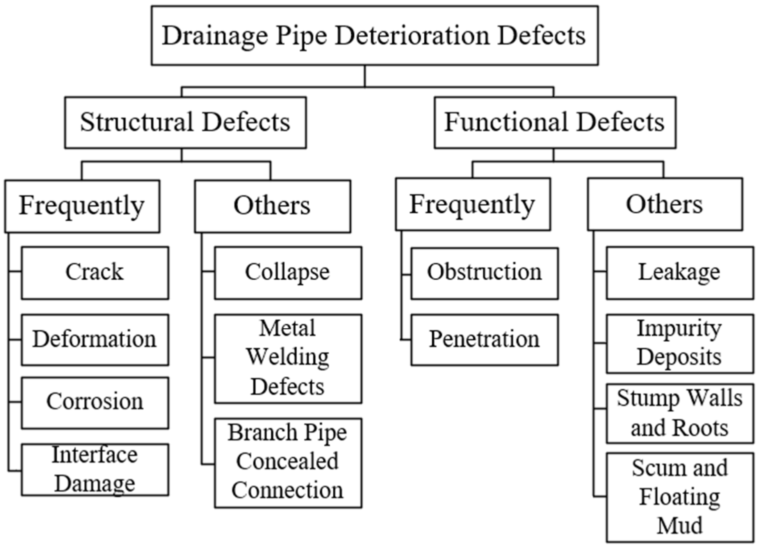
### *2.5. Summary and Pipeline Defects*

We summarize the important information of the above-mentioned manuals and standards in Table 1.

**Table 1.** Summary of important manuals and standards.

| Manual or Standard | Country | Severity Classifications | Defect Classifications |
|---|---|---|---|
| PACP | North America | 1 to 5 (1 means the minor defects, and 5 means worse situation) | Structural defects and Operation and Maintenance defects |
| SRM | UK | 1 to 5 | Structural defects and Service defects |
| ACCEM | Australia | Used to be 1 to 3, and then revised to 1 to 5 | Structural defects and Hydraulic defects |
| CJJ181-2012 | China | 1 to 5 | Structural defects and Functional defects |

On this basis, we have combined the PACP, SRM, ACCEM, and CJJ181-2012 and summarized the literature [19,24,25] and engineering experience to collate common drainage pipe deterioration and breakage patterns (Figure 2). To improve the process efficiency and model accuracy, the common deterioration and breakage patterns are usually analyzed first in the evaluation of drainage pipeline conditions.




- Crack is divided into fracture, split, and crushing.
- Interface Damage is divided into mismatch, heave, disconnect, and interface material shedding.
- Leakage is divided into seepage and infiltration.

**Figure 2.** Drainage pipe deterioration and breakage patterns collated from sources given in the above.

## 3. Pipeline Condition Influencing Factors

The deterioration and breakage of water and drainage pipelines is a very complex process, and the use of a single influencing factor to describe the evaluation of pipeline condition is inadequate [26,27]. The selection of meaningful influencing factors can systematically describe the underground pipeline deterioration and breakage process mechanistically, and significantly improve the expression of pipeline deterioration and breakage prediction models [19,28]. A large number of studies have been conducted that summarize and systematically elaborate the classification of influencing factors for pipeline condition evaluation, but due to the variability of data and standards in different regions, these studies do not have a uniform way of classifying the influencing factors for pipeline condition.

In 2001, Davies et al. [29] studied the causes of structural breakage and collapse damage of rigid pipelines from three aspects: construction factors, local external factors, and other factors. They summarized the factors influencing underground pipeline condition in a more systematic way, and then conducted a number of mechanistic studies on this basis. At the beginning of the 21st century, Kleiner and Rajani [30–32] tried to distinguish the influencing factors of pipeline condition by time correlation, and in 2007, they pioneered the classification of influencing factors into static factors (related to the nature of the pipeline and the type of installation), dynamic factors (related to the soil around the pipeline or the operating environment), and operational factors (including replacement rate and maintenance methods). The above approaches provide an important reference perspective for pipeline construction, investigation, evaluation, and operational rehabilitation, but in practice, there are problems of redundant and complex influencing factors and large deviations from the norm.

In 2002, the Canadian National Sustainable Municipal Infrastructure [33] issued the first practical guide that proposed classifying the factors influencing pipeline conditions into physical, environmental, and operational factors. Al Barqawi and Zayed [13] integrated and simplified the three categories of factors to improve the applicability of this classification. Salman [34], Kley and Caradot [28], and Hawari et al. [35] further added to this approach to make it the mainstream classification model of factors. In this paper, we follow the classification model of Al Barqawi and Zayed and synthesize the literature [17,18,29,35,36] to summarize the classification of factors influencing drainage pipeline condition and pipeline damage models as shown in Table 2, where those marked with * are the important influencing factors.

**Table 2.** Drainage pipe condition factors and types of mechanism.

| | Influencing Factors | Mechanism |
|---|---|---|
| Physical factor | Pipe age * | The mechanism of pipe age influence can be explained by the "bathtub curve" [37]. Usually, the older the pipe is, the more likely it is to break [16,38,39]. |
| | Pipe diameter * | It is generally believed that pipes with larger diameters are less prone to deterioration and breakage [29,40], and pipes with diameters less than 200 mm are more prone to breakage [41]. |
| | Pipe material * | (i) The selection of pipes has a strong historical influence [17]<br>(ii) Concrete, PVC, and other corrosion-resistant pipes are being used more and more frequently [2], and in general, as the most widely used pipe, concrete pipes have strong corrosion resistance and a lower deterioration and breakage rate [16,42] |
| | Pipe length * | (i) The effect of pipe length on the condition of pipes is related to pipe joints and lateral structures [15,16]<br>(ii) Longer pipes are more prone to clogging or settling [16]<br>(iii) Bending stresses due to increased pipe length are responsible for the susceptibility of pipelines to structural breakage [15,43] |
| | Pipe slope | (i) Longer retention time of sewage in gently sloping pipes leads to the generation of large amounts of hydrogen sulfide gas in the pipes, inducing pipe breakage [16,44]<br>(ii) Pipes with large inclined angles usually have large water flow velocities, and the water flow impacts the pipe structure, thus inducing pipe structure damage [45,46] |
| | Installation quality | There is a greater correlation between the normative standards of the pipe installation formation and the type of pipe [27,28] |
| | Pipe depth | (i) Shallow pipeline burial depth is shallow and vulnerable to ground load pressure and tree root growth [18,47]<br>(ii) Increased burial depth of the pipeline indicates an increase in the static load overlying the pipeline while increasing the possibility of the groundwater table affecting the pipeline [38,48] |
| | Pipe shape | Typically, round pipes are more resistant to deterioration breakage than square pipes [49] |

**Table 2.** *Cont.*

| | Influencing Factors | Mechanism |
|---|---|---|
| Physical factor | Coating and lining | Coatings and linings have multiple limitations for historical reasons, and usually, coated and lined pipes are less likely to deteriorate and break down [13] |
| | Joint type | (i) The damage probability of pipe joints increases significantly with time, and after some time, the damage probability of pipe joints of some materials may even be significantly greater than that of pipe sections [50]<br>(ii) Rigid pipe joint defects usually originate from improper installation, and the movement of the upper load is more likely to induce leakage and joint fracture in rigid joints [50]<br>(iii) Flexible pipe joints can withstand the effects of small displacements, but improper installation or multi-directional upper load movement can lead to flexible pipe joint fracture [51] |
| Environmental factor | Seasonality * | (i) Extreme weather and sudden climatic changes can catalyze pipe deterioration and breakage with variability in the manifestations of different pipes [17,52,53]<br>(ii) Changes in humidity and temperature due to seasonal changes can affect the condition of the pipe, and it is generally believed that there is a significant decrease in humidity and increase in temperature in summer and autumn, leading to more vulnerable pipe breakage during this period [54,55] |
| | Soil condition * | (i) Soil properties such as the type of buried soil and fracture potential of the pipeline have a great influence on the pipeline [29,56]<br>(ii) Soil compression and consolidation drainage due to ground load movement, as well as migration loss of fine soil particles triggered by groundwater seepage, can affect the condition of the pipeline [57,58] |
| | Construction location | (i) The overlying pressure of the pipeline and the traffic pressure in the pipeline construction area jointly affect the condition of the pipeline [29,59]<br>(ii) Construction locations with more trees or deeply buried foundations can easily trigger foreign object penetration [16,28] |
| | Groundwater level | Infiltration is likely to occur when the groundwater level is higher than the pipeline location, while the increase in pore water pressure brought about by the rising water level leads to a decrease in the effective stress of the soil, increasing the risk of breakage of the pipeline structure [29,60] |

**Table 2.** *Cont.*

| | Influencing Factors | Mechanism |
|---|---|---|
| Operating factor | Pipe type * | (i) Drainage pipes can be divided into sewage pipes, stormwater pipes, and rainwater pipes according to their uses, and the degree of deterioration and breakage of pipes of different use types varies greatly [29,39,61]<br>(ii) Pipe use generally determines the quality of water in the pipe, and the quality of water affects the condition of the pipe [28,62] |
| | Maintenance history * | (i) The pipeline areas where defects have occurred are prone to secondary damage, and the damage forms or triggering factors have spatial and temporal clustering with the causal mechanisms of the initial pipeline defects [63,64]<br>(ii) Human activities during operation and maintenance can affect the pipeline condition, such as dredging before pipeline cleaning and testing [29,65] |
| | Flow rate | (i) Drainage pipes are susceptible to fatigue damage under the influence of cyclic water pressure, and the phenomenon is more obvious in pipes with defects [66]<br>(ii) The increase in the instantaneous drainage flow rate will lead to a great impact on the pipe, and fragile parts such as pipe joints and existing pipe defects are prone to breakage as a result [67] |

The items marked with * are the important influencing factors.

## 4. Drainage Pipe Condition Prediction Models

The purpose of a drainage pipe deterioration and breakage prediction model is to analyze the collected pipeline data information to make short-term or long-term pipeline condition predictions, provide decision-makers with accurate pipeline condition reports, and provide scientific planning suggestions for future pipeline investigation, operation, and maintenance [68]. In 1990, Bao and Mays [69] established a distribution system node and system hydraulic reliability assessment method based on Monte Carlo simulations. The analysis and extension of the existing system opened up research in drainage pipe deterioration and breakage prediction models. Since then, advances in computer technology and updates in algorithmic models have provided more options for the selection of prediction models and greatly enriched the drainage pipeline condition evaluation system.

Over the past 30 years, researchers have done a lot of work to elaborate and improve drainage pipe condition evaluation systems. Table 3 shows the classification types of some drainage pipe deterioration and breakage prediction models in chronological order. Combining existing classification methods taken from the literature, each classification method is integrated and organized into the classification method, as shown in Figure 3. Many models that have been studied or applied are listed in Figure 3, and the models are classified into typical models and other models according to how widely they have been studied (e.g., Other Models for Statistical models, whose studies appear less frequently and are less recognized). In the following section, we focus on the typical models and the focused models.

**Table 3.** Classification of existing drainage pipes deterioration assessment models.

| Authors | Year | Classification |
|---|---|---|
| Dasu and Johnson [70] | 2003 | Data-driven and Expert-driven models |
| Yang [71] | 2004 | Physical, Statistical, and AI models |
| Morcous and Lounis [72] | 2005 | Deterministic, Probabilistic, and Soft-Computing models |
| Tran [73] | 2007 | Model-driven and Data-driven types |
| Ana and Bauwens [74] | 2010 | Pipe group model (Consider pipe sections with similar pipeline characteristics throughout the network or in regional clusters)Pipe level model (Pipeline characteristics are used as covariates to analyze the state of a pipeline in a point area for independent analysis and evaluation of a single pipeline segment) |
| Morcous and Lounis [72], Kley and Caradot [28], Salihu et al. [75] | 2005 2013 2022 | Deterministic model Deterministic, statistical, and AI models |

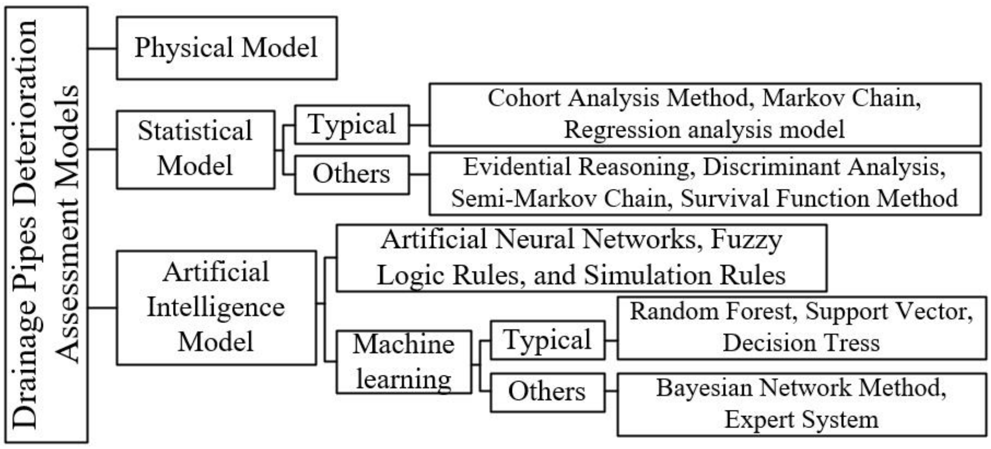



**Figure 3.** Classification of existing drainage pipes deterioration assessment models.

### *4.1. Physical Models*

Physical models, also known as deterministic models, involve the construction of a quantitative expression of mathematical formulae for influencing factors and pipeline health states based on the analysis of pipeline breakage mechanisms and predict pipeline damage patterns under changes in influencing factors [28,35]. Rajani and Kleiner [76] considered that the damage mechanisms of physical models involve three aspects: (i) structural characteristics of the pipeline (e.g., materials); (ii) internal and external pipeline loads (e.g., traffic load and drainage flow rate); and (iii) material corrosion deterioration (e.g., internal and external chemical and environmental corrosion). Some typical physical models are shown in Table 4.

**Table 4.** Typical examples of physical models.

| Authors | Model Name | Describe |
|---|---|---|
| König [77] | ExtCorr | Predicting external deterioration of concrete pipes by assessing soil moisture, corrosion, and cement quality |
| Vollersten and König [78] | WATS | Describe the joint mechanism of compounds in wastewater and organic transformation processes on the internal deterioration state of pipes using nonlinear differential equations |

The main drawbacks of physical models are: (i) only the current state of the pipe is considered, ignoring the influence of the history of pipe deterioration failures [78]; (ii) the model assumptions need to be concise, and the model accuracy depends on the correct identification of the influencing factors [79]; and (iii) the complex process of drainage pipe deterioration and breakage cannot be described, and the model interpretation is low [73].

### *4.2. Statistical Models*

Researchers have attempted to model the condition of the pipeline with a set of explanatory covariates, which has led to the gradual development of statistical models. Among the statistical models that have been widely applied are the cohort survival method, Markov chains, and logistic regression models [74,80].

#### 4.2.1. Cohort Survival Models

The cohort survival method is an important approach to the survival analysis method that uses similar grouping data to predict the probability of pipe breakage, life expectancy, and fracture clustering [27]. The basic assumption of the method is that the pipeline cluster survives for a number of years in some state with a certain probability, and gradually evolves from that state to the worst state [81]. This evolution towards the worst state is usually described using a transition function, as in Equation (1) [82,83]:

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

where:

$S(t)_{i\to i+1}$: the portion of the pipe with pipe age t that survives to state $i$ or worse.

$a$: the aging coefficient ($a$ = 0 means no aging occurs, and a larger value of a means a smoother transition).

$b$: the transition parameter (a larger value of $b$ indicates a faster transition).

$c$: the resistance time, which determines the timeframe in which the pipeline will not deteriorate further in the expected state.

The use of the transition function requires the year of installation, the year of inspection, and the pipe condition data for the typicality pipes in the cluster. The curves generated by the transition function can predict the remaining life of the pipeline. A representative example is the transition function and its curve established by Hörold in 1998 [84], as shown in Figure 4, which shows that for a group of pipes that have been in use for about 50 years and are categorized as having a health status of 2 to 3 after CCTV inspection, the earliest pipe in the group to reach class 5 (the worst condition) has a life of 48 years; the last pipe in the group to reach class 5 status has a remaining life of 105 years, and the average remaining life of this group of pipes is 80 years.

The cohort survival method is sensitive to pipe-age analysis and can be used to deduce the most likely time in the future for the target pipeline to enter a poorer health state using existing data, and can also provide an accurate schedule for pipeline maintenance and rehabilitation [84–87]. Ana et al. [88] and Laakso et al. [89] developed a cohort survival method-based prediction model to investigate the sensitivity of pipe age to other influencing factors that showed a high sensitivity of pipe age to pipe type and pipe length. They pointed out that the reliability of the model is greatly influenced by the accuracy of the data.

#### 4.2.2. Markov Chains

In a Markov chain, the probability of each event depends only on the state of the previous event without considering the influence of past events, a property also known as "memorylessness". The basic assumption of a Markov chain-based pipeline prediction model is that the conditional probabilities do not vary with time. The conditional probabilities are given in Equation (2) [45]:

$$P(X_{t+1} = j | X_t = i) = p_{ij} \tag{2}$$

where $p_{ij}$ is the transition probability, which is the probability that part of the pipeline transitions from state $i$ at moment $t$ to state $j$ at moment $t+1$. Usually, the pipeline health state is divided into five stages: stage 1 is the best state, which refers to the ideal state where the pipeline has just been installed and can be put into normal use, and stage 5 is the worst state, in which there is an urgent need to replace the pipeline immediately. From these five pipeline health states can be obtained a $5 \times 5$ matrix $M$, called the transition probability matrix, as in Equation (3) [90]:

$$M = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} & p_{1m} \\ 0 & p_{22} & p_{23} & p_{24} & p_{2m} \\ 0 & 0 & p_{33} & p_{34} & p_{3m} \\ 0 & 0 & 0 & p_{44} & p_{4m} \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (3)$$

where $p_{ij} = 0$ when $i > j$ indicates that the pipeline will only get progressively worse without human intervention [35]. The pipeline health state at moment $t+1$ can thus be calculated from the conditional probability at moment $t$, as shown in Equation (4), while the state expression at moment t is as in Equation (5):

$$P^{t+1} = P^t \times M \quad (4)$$

$$P^t = \left[p_1^t,\ p_2^t, p_3^t, p_4^t, p_5^t\right] \quad (5)$$

Markov chains can calculate the probability of pipe evolution to a worse state and can also be used as time-based models to calculate the time probability distribution between different pipe states [91]. In 2001, Wirahadikusumah et al. [56] combined nonlinear optimization and Markov chains to establish a drainage pipe deterioration and breakage prediction model and proved the sensitivity to pipe age of Markov chains. Since then, many studies have gradually improved the application form and interpretation of Markov chains [85,92], and some researchers have established Markov chain engineering application models [90,92–94], which have gradually established a mature and applicable drainage pipe health state evaluation O&M system.

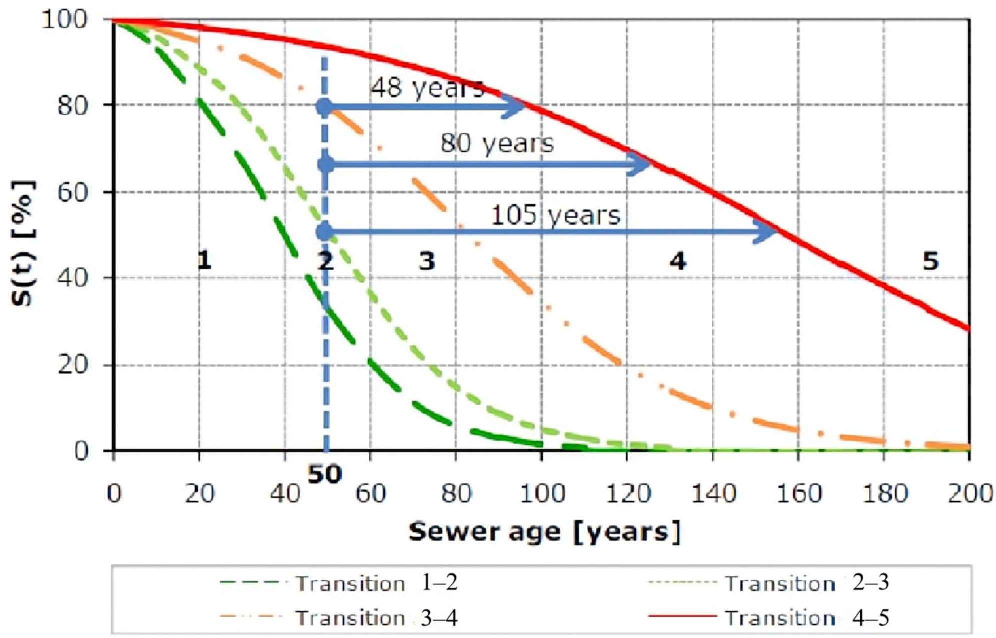



**Figure 4.** Transition functions for a Norwegian network and prediction of the sewer's remaining service life. Adapted with permission from Ref. [84]. 2023, SINTEF.

#### 4.2.3. Logistic Regression Models

Logistic regression models are a form of regression analysis model that use logistic curve fitting to evaluate pipeline conditions by analyzing the relationship between multiple independent variables and sub-attributable dependent variables [19]. They are usually described using Equation (6):

$$\log\left[\frac{\pi}{1-\pi}\right] = \log\left[\frac{p(y=1|x_1,\cdots,x_n)}{1-p(y=1|x_1,\cdots,x_n)}\right] = \alpha + \sum_{j=1}^{p}\beta_j X_j \quad (6)$$

where:

$\pi$: the state of the pipe is healthy—conversely $1-\pi$ means that the pipe has suffered damage.

$X_j$: a set of independent variables (influencing factors, such as pipe age and pipe diameter).

$\beta_j$: the regression coefficient.

$\alpha$: the intercept parameter.

Logistic regression models have grown into a relatively mature system through continuous iteration and improvement across several decades of development. A logistic regression model is established by identifying the influencing factors and collecting drainage data in a targeted manner, then analyzing the effect of the influencing factors in the model to rank the important influencing factors and comparing them with a validation set to determine the model accuracy [39,42,95,96]. Logistic regression models have also been applied to validate the contribution of new influencing factors to the deterioration breakage of drainage pipes [60,97].

#### 4.2.4. Comparative Analysis of Previous Models

The advantages and disadvantages of the cohort survival method, Markov chain, and logistic regression model are summarized and analyzed in Table 5.

**Table 5.** Summary of advantages and disadvantages of several typical statistical models.

| Model Type | Advantages | Disadvantages |
|---|---|---|
| Cohort survival model | (i) Concept is easy to understand and easy to calculate<br>(ii) Transition curve gives a good explanation of the deterioration and damage process of the pipeline<br>(iii) Beneficial to the cost calculation of pipeline maintenance and repair [74] | (i) The data demand is huge and usually not easy to meet [98]<br>(ii) Pipes that have undergone deterioration and breakage are easily ignored in model calculations, resulting in large predicted pipeline life [99] |
| Markov chain | (i) The model can be greatly simplified by reducing the number of similar pipes when calibrating the transition function [28]<br>(ii) The most likely time of pipe deterioration can be predicted, and the model is very flexible | (i) The pipeline needs to be classified and grouped, and each group of models requires sufficient data for simulation validation<br>(ii) The conditional probability matrix is complex to build [68] |
| Logistic regression model | (i) The concept is simple and easy to understand, and the model is powerful in prediction<br>(ii) It can analyze the degree of influence of influencing factors on the deterioration and breakage of the pipeline<br>(iii) The model mechanism is highly explanatory and can decompose the pipeline deterioration and damage process<br>(iv) The model can be built without the prerequisite assumptions [34,100] | (i) The data requirements are extremely high<br>(ii) The linear nature of logistic regression is not flexible enough to identify nonlinear decision boundaries and more complex relationships [35,68] |

### *4.3. Artificial Intelligence (AI) Models*

AI modeling refers to the use of artificial neural networks (ANNs) with rule-based models for problem analysis and interpretation [35]. In pipeline condition evaluation, ANNs learn the deterioration damage of the pipeline from existing data, study the mathematical logic relationship between the independent (each influencing factor) and the dependent (pipeline condition level) variables, and predict the possible deterioration damage of the pipeline through this process [73].

#### 4.3.1. Artificial Neural Networks (ANNs)

ANNs are a simulation of the human nervous system, consisting of layers of artificial neurons that mimic the human brain's ability to recognize judgments and predict certain possible outcomes by learning from existing knowledge [101]. In drainage pipe condition evaluation, backpropagation and probabilistic neural networks are usually used to build pipe deterioration breakage prediction models [16,28,35,73,102].

(1) Backpropagation neural networks

A backpropagation neural network is usually divided into an input layer, a number of hidden layers, and an output layer (Figure 5) [73]. The nodes in the input layer consist of the influencing factors describing the health state of the pipe, denoted by $X_i$; the nodes in the hidden layer(s) receive the signals from the input layer and multiply them by the relevant connection weights in aggregate to generate the output signals using a predefined mathematical function, and the neurons in the output layer analyze and define the drainage pipe health state type based on the signals from the hidden layer(s). The training of the neural network is realized by the model learning the data iteratively and continuously cycling the output results, usually by reducing the error between the observed and predicted values to minimize prediction errors [28].

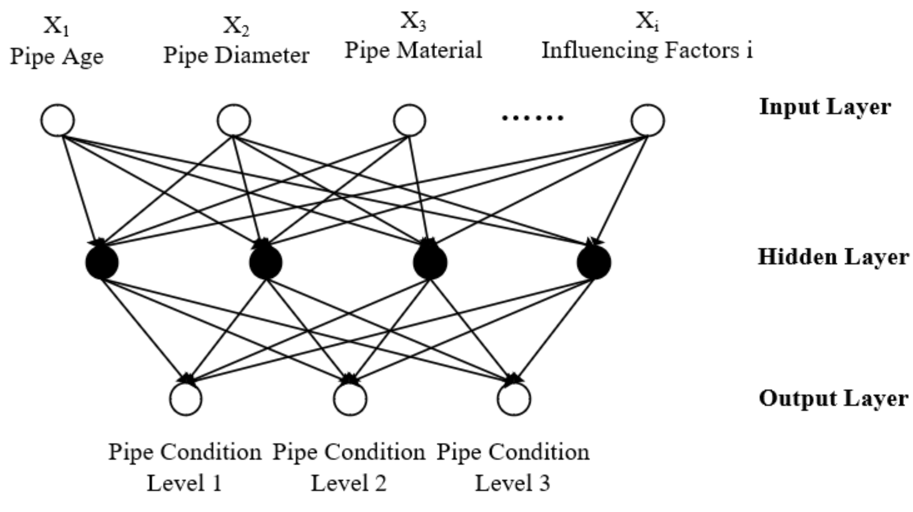



**Figure 5.** Schematic presentation of a backpropagation neural network with a single hidden layer.

(2) Probabilistic neural networks

Probabilistic neural networks are a special form of ANN that classify the inputs into different classes based on Bayesian classification [103]. A probabilistic neural network is divided into an input layer, a pattern layer, a summation layer, and an output layer (Figure 6 [104]). The input layer functions in the same way as the input layer of the backpropagation NN; the values of the nodes in the pattern layer are the dot product values of the input vector, X, and the weight vector; the nodes in the summation layer receive the corresponding output values from the pattern layer and calculate the results using the probability density function (the formula of the probability density function for category i is shown in Equation (7)); the output layer receives the output values from the summation layer and assigns the conditions by applying the Bayesian decision rule (Equation (8)).

$$f_i(x) = \frac{1}{(2\pi)^{\frac{\pi}{2\sigma^n}}} \frac{1}{M_i} \sum_{j=1}^{M_i} e^{-\frac{\left(x-x_j^{(i)}\right)^T \left(x-x_j^{(i)}\right)}{2\sigma^2}} \tag{7}$$

where:

$x_j^{(i)}$: the input vector of the $j$th sample in class $i$ of the training set.

$n$: the dimensionality of the input vector.

$M_i$: the number of training samples in category $i$.

$\sigma$: the smoothing parameter; $\sigma$ is the most important parameter to be determined; different values of $\sigma$ need to be selected for training tests when building the model, and the optimal $\sigma$ value corresponding to the one that produces the smallest error value is chosen [105].

$$h_1 f_1(x) > h_2 f_2(x) \tag{8}$$

where:

$x$: the n-dimensional input vector.

$h_1$: the prior probability of category $i$.

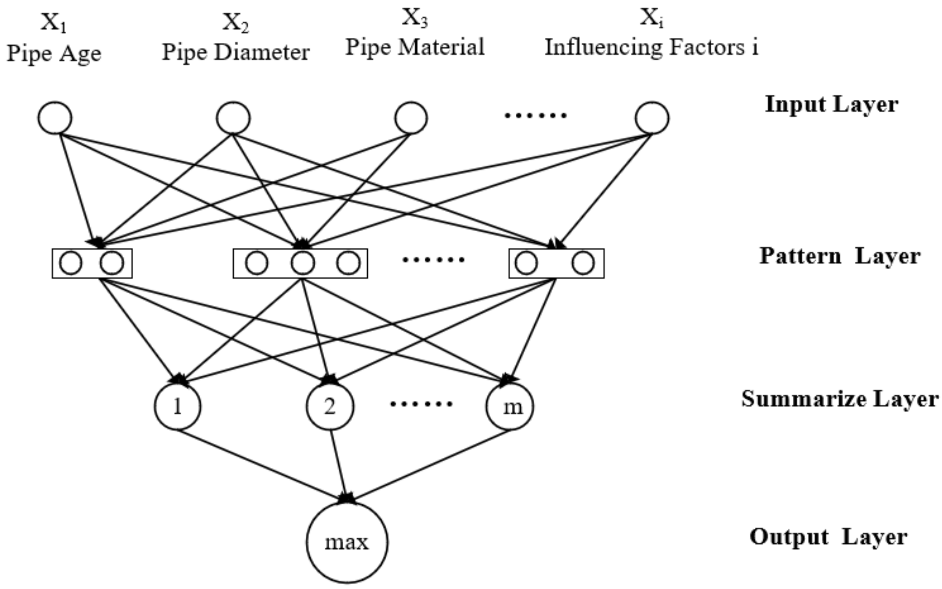



**Figure 6.** Schematic presentation of a probabilistic neural network.

ANNs have become the main approach for modeling in recent years. The selection of influencing factors with important characterization in drainage pipes for targeted data collection is the key to establishing ANN models. Most of the models in the literature select mostly physical factors, such as pipe age, pipe length, pipe diameter, pipe material, pipe inclination, and pipe burial depth [38,106,107]. However, some studies also include important environmental and operational factors in the scope of the application [108–110]. They have achieved good model prediction results, but there is still a lot of room for progress in research on models incorporating environmental and operational factors.

The advantage of ANNs is that they are extremely capable of dealing with complex and variable pipeline health states and ambiguous influencing factor data. They can also handle scale and ordinal data. The ANN model is a practical alternative to the theoretical model if the relationship between the dependent and independent variables is poorly explained [35,73]. The disadvantage of ANN is that the mechanism of pipe deterioration and breakage is poorly explained [28].

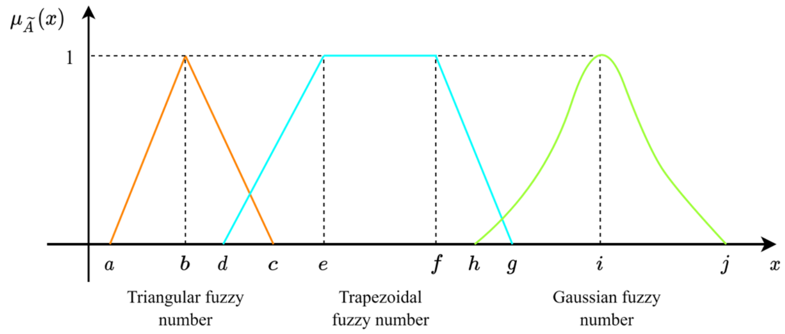
#### 4.3.2. Fuzzy Logic Rules

Fuzzy logic rule is a mode of application of fuzzy set theory, which was proposed by Zadeh in 1965 to solve the problem of uncertainty in practical applications [111]. A fuzzy set $\widetilde{A}$ in a universe $X$ can be expressed as follows:

$$\widetilde{A} = \{x,\ \mu_{\widetilde{A}}(x) | x \in X\}, \tag{9}$$

where $\mu_{\widetilde{A}}$ is between $[0,\ 1]$, and $\mu_{\widetilde{A}}(x)$ is the degree of subordination to $\widetilde{A}$ among the values of $x \in X$.

Fuzzy sets are usually described using the triangular fuzzy number, trapezoidal fuzzy number, and Gaussian fuzzy number. The triangular fuzzy number and trapezoidal fuzzy number are non-continuous functions, and the Gaussian fuzzy number is a type of continuous function, as we can see in Figure 7. The fuzziness is best characterized by the above three functions, and in other words, we can describe that the membership function represents the degree of truth in fuzzy logic [112].




$$\mu_1(x) = \begin{cases} \frac{x-a}{b-a}, & a \le x \le b \\ \frac{x-b}{c-b}, & b \le x \le c \\ 0, & else \end{cases} \quad \mu_2(x) = \begin{cases} \frac{x-d}{e-d}, & d \le x \le e \\ \frac{x-f}{g-f}, & f \le x \le g \\ 1, & e \le x \le f \\ 0, & else \end{cases} \quad \mu_3(x) = \begin{cases} e^{-\frac{(x-i)^2}{2\sigma_1^2}}, & h \le x \le i \\ e^{-\frac{(x-i)^2}{2\sigma_2^2}}, & i \le x \le j \\ 0, & else \end{cases}$$

**Figure 7.** Schematic diagram of Triangular fuzzy number, Trapezoidal fuzzy number, and Gaussian fuzzy number.

In general, the models based on fuzzy logic rules follow the term "antecedent proposition", which can describe the relationships between variables by fuzzy if-then rules. Mamdani antecedent proposition as a typical antecedent proposition can effectively solve the qualitative and highly uncertain knowledge problem, and its if-then formula is shown in Equation (10) [32].

$$R_i : if\ x\ is\ A_j\ then\ y\ is\ B_k, \quad i = 1, 2, \ldots, l,\ j = 1, 2, \ldots, M,\ k = 1, 2, \ldots, N \tag{10}$$

where,

$x$ is the input (antecedent) linguistic variable,
$y$ is the output (consequent) linguistic variable,
$A_j$ is $M$ antecedent linguistic constant in a set $A$,
$B_k$ is $N$ consequent linguistic constant in a set $B$.

The values of $x$, $y$, $A_j$, and $B_k$ are obtained from predefined sets and rules that define the model [35], and the membership function can be described by the expression in Figure 7.

To identify the deterioration of drainage pipelines, the models based on fuzzy logic rules are used to overcome data scarcity and imprecision. In modeling applications, fuzzy logic rules are often used in conjunction with other models to fuzzify the influencing factors of drainage pipelines. Neuro-Fuzzy Approaches [113], fuzzy rules-based Markovian process [32,114], and fuzzy logic rules-based multiple linear regression and ANN models [115] have been developed in the past several years. It can be seen that fuzzy logic rules have become one of the main tools for model building and are widely used in the joint application of various models.

The advantages and disadvantages of fuzzy logic rules are very obvious. Its main advantages are its simple structure and ease of interpretation, no need for precise data sources, and its ability to integrate effectively with other models. Its major disadvantages are that it is difficult to express precisely, and it has a large degree of likelihood hypothesis in the opinion of a significant number of researchers [116,117].

#### 4.3.3. Simulation Rules

The models based on simulation rules are used to represent real-time engineering systems by generating large numbers of outcomes in order to estimate outcomes as in reality [118]. In a rule-based simulation model, the state of the system and state transitions are collectively referred to as events that define the dynamic form of the model, where the state of the system is defined by the characteristic properties of a collection of objects called "entities", and the change of state is referred to as a state transition [119].

In 2004, Ruwanpura et al. [120] developed a rule-based model to determine the condition of sewer pipelines and the probability that the pipe can remain in its current condition based on a 5-year increment. But in general, such models are not replicable, the biggest reason being that a sufficient amount of real-time data for the pipeline is extremely difficult to obtain. Based on the above limitations, some researchers have adopted the idea of introducing expert subjective evaluation to solve the problem of missing data to some extent. Hawari et al. [43] adopted the Fuzzy Analytical Network Process for the evaluation of influencing factors. The overall condition of the pipeline is determined by simulating the product of the relevant weights and effect values of different factors over several iterations.

The biggest reason why the models based on simulation are still not widely used is that the demand for data is difficult to be satisfied. With small samples of data, the accuracy of the model is easily influenced by different data trends [35].

#### 4.3.4. Machine Learning (ML) Models

ML models learn directly from existing data and predict the future state of the pipeline by exploring different prediction structures and algorithms [121].

(1) Random forest

Random forest is a method for generating numerous independent classification trees based on random samples, which also allows for the selection of only a subset of variables to form a classification tree, adding a layer of randomness to the creation of the model [122]. In drainage pipe condition evaluation, the predictor variables may have complex dependencies, and these relationships are likely to be nonlinear, which creates suitable conditions for the application of random forest models. Examples of random forest models in drainage pipe deterioration and breakage prediction models are given in Table 6.

**Table 6.** Examples of random forest models.

| Year | Authors | Describe |
|---|---|---|
| 2014 | Harvey and McBean [123] | A random forest model was developed using pipeline data from Guelph, Canada, and ROC curves were used to establish alternative cut-off points for prediction probabilities, proving that the random forest model is an "excellent" choice for predicting pipeline condition |

**Table 6.** *Cont.*

| Year | Authors | Describe |
|---|---|---|
| 2018 | Laakso et al. [15] | A random forest model was developed with a logistic regression model, and the results showed that random forest had higher accuracy. It was also found that although deformation, root intrusion, and pipe surface defects were not significantly characterized in the set of datasets, the random forest still had higher accuracy in predicting the results of the above damage patterns |
| 2018 | Wang et al. [124] | Proposed a random forest fusion-based pipeline leakage diagnosis method, the algorithm improves the accuracy by 2.2% and 6.4% compared to the backpropagation neural network model and the D-S evidence theory model of support vector machine, respectively |
| 2020 | Li [125] | A random forest model is established based on the monitoring data of a pipeline network in a park in Suzhou, and the univariate and inter-variate analysis is used to obtain the feature importance and contribution rate, to give the decision path of the pipeline section, to improve the interpretability of the model, and to prove the superiority of the random forest algorithm |

(2) Support vector machines (SVMs)

An SVM aims to find a hyperplane such that the points of different categories in the training sample set fall exactly on both sides of the hyperplane, and also requires that the blank area on both sides of the hyperplane is maximized [126]. Figure 8 illustrates the principle of applying SVM in two-dimensional space. Typical SVM models in drainage pipe deterioration breakage prediction models are shown in Table 7.

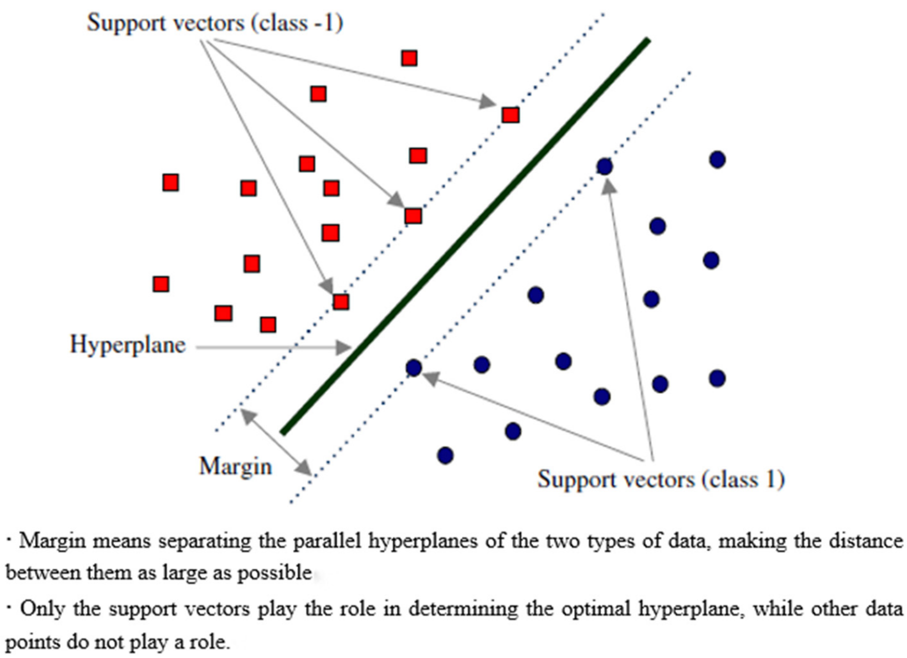



**Figure 8.** Application principle of SVM in two-dimensional space.

**Table 7.** Examples of support vector machine models.

| Year | Authors | Describe |
|---|---|---|
| 2011 | Mashford et al. [127] | A support vector machine model was established by selecting influencing factors such as pipe age, pipe diameter, road type, pipe inclination angle, pipe, soil type, etc. The accuracy of the model reached 91%, but due to the lack of sufficient data, the model still has room for improvement |
| 2014 | Harvey and Mcbean [128] | Using pipeline data from Guelph, Canada, a support vector machine model was built using selected influencing factors such as pipe age, pipe, and pipe type, with a model accuracy of 76%. |
| 2021 | Zhou et al. [129] | Combining kernel density estimation and support vector machine algorithm to construct a drainage pipe deterioration and breakage prediction model, the model accuracy reaches 91%. Applying the model to the pipeline in Yangpu District, Shanghai, it can effectively identify the pipe sections with a lower safety level |
| 2021 | Chen and Wang [130] | To solve the time-consuming problem of least squares support vector machine, an adaptive genetic algorithm is used to optimize LSSVM parameters and establish a pipeline health state prediction model with overburden depth, pipe diameter, water pressure, and road grade as inputs, and the results show that the new model takes less time to model and has better prediction capability |

(3) Decision trees

Decision trees predict the target variable using a set of rules arranged in a tree structure (Figure 9). During the training process, the rules are built starting from the root node, where all observations are initially assigned. The root node is then split into several decision node branches according to the values of the predicted variables. Under each partition, the observations of the higher-level nodes are allocated to the lower-level nodes. This is repeated recursively for each branch until all observations on a decision node have the same classification result [131]. Typical decision tree models in the drainage pipe deterioration breakage prediction model are shown in Table 8.

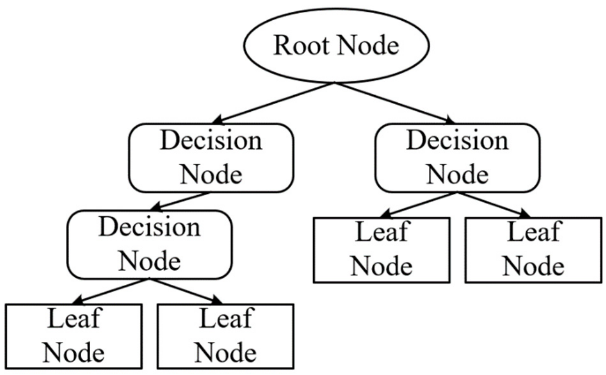



**Figure 9.** Schematic diagram of a decision tree model.

**Table 8.** Examples of decision tree models.

| Year | Authors | Describe |
|---|---|---|
| 2008 | Chen et al. [132] | Analyze the aging and leakage data of Beijing pipelines from 1987 to 2005, apply a decision tree algorithm to develop a pipeline prediction model based on pipe age and pipe diameter, and predict the distribution of aging and leakage of pipelines in Beijing in 2008 through ArcGIS |
| 2013 | Syachrani et al. [131] | A decision tree model based on background information survey and pipe inspection data is selected for pipe age, pipe diameter, pipe length, pipe inclination, and number of trees, and the model has good performance in predicting the pipe age of drainage pipes |
| 2014 | Harvey and McBean [48] | Using pipeline data from Guelph, Canada, a decision tree and a support vector machine model were built using selected influencing factors such as pipe age, pipe, and pipe type, and the results showed that the support vector machine model was more accurate |
| 2022 | Meydani et al. [133] | A Bayesian decision model based on decision tree theory is developed to facilitate the structuring process of the initial problem in a decision process with uncertainty. Applying the model to a water distribution network architecture in Sweden, the results show that the cost of human intervention and leakage probability have a significant impact on the model performance and O&M decisions |

## 5. Model Validation

Model validation is a necessary step in determining the model's reliability and creating a link between practical engineering applications and theoretical studies. Validation of a model typically refers to confirmation of the model's prediction accuracy span and generalization ability [134]. The most direct method of validation is to use actual data to test the predictability of the results [135]. During data processing, we set aside a small portion of the data (e.g., 30% or 35%, etc.) and summarize the model's accuracy by comparing that raw data to the accuracy of the final prediction.

### *5.1. Validation Methodologies*

Many validation methodologies have been developed, typically at the pipe group level, with the goodness-of-fit being the most commonly used to predict the number of deteriorated pipes at a given time under large sample conditions. At the pipe level, researchers typically use the confusion matrix to describe whether or not the model prediction is accurate, and Root Mean Square Error to describe the model's prediction accuracy [19].

#### 5.1.1. Goodness-of-Fit Test

Goodness-of-fit is a statistical test methodology that is used to determine how well the observed data works in the model. It can fairly summarize the difference between the model's predicted and actual data. In the goodness-of-fit literature, three main classifications have been developed: the chi-square, the Kolmogorov-Smirnov, and the Anderson-Darling. The three methods described above are detailed in Table 9.

**Table 9.** The three approaches to goodness-of-fit [136–141].

| Approach | Description | Application Scope | Merits |
| --- | --- | --- | --- |
| The chi-square | It evaluates whether proportions of categorical or discrete outcomes in a sample follow a population distribution with hypothesized proportions. | • Sampling method is random.<br>• Predictor variables are categorized.<br>• A sufficient sample size is required to make the chi-square approximation valid. | • It can be easily calculated and concluded.<br>• The Chi-Square test provides an additive property. This allows the researcher to add independent results to the sample of interest.<br>• This test is based on the observed frequencies rather than on parameters such as mean and standard deviation. |
| Kolmogorov-Smirnov | It assesses whether a single sample could have been sampled from a specified probability distribution | • The predicted variable is continuous | • It does not make any assumptions about the distribution of the data.<br>• There is no restriction on the sample size, and small samples are acceptable. |
| Anderson-Darling | It is used to compare the fit of the observed cumulative distribution function with the expected cumulative distribution function. | • The A-D test is proposed for the continuous as well as discrete cases | • It does not make any assumptions about the distribution of the data.<br>• There is no restriction on the size of the sample. Small samples are acceptable. |

### 5.1.2. Confusion Matrix

A confusion matrix, also known as an error matrix, is a method for summarizing a classification algorithm's performance [142]. The matrix's rows represent instances in the actual class, while the columns represent instances in the predicted class [143]. Four scenarios can be obtained by comparing the predicted results to the actual data [19], and we usually use Figure 10 to describe these situations:

- True positive (TP): the model predicts the good pipe condition correctly.
- True negative (TN): the model predicts the poor pipe condition correctly.
- False positive (FP): the model predicts a poor pipe condition as a good condition.
- False negative (FN): the model predicts the active condition as a poor condition when it is not.

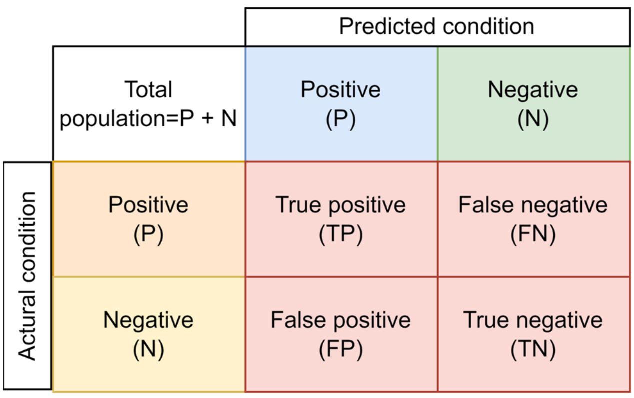



**Figure 10.** Comparison results of predicted condition and actual condition.

*5.2. Validation Results in Typical Case Studies*

5.2.1. Case Studies

Many researchers have used actual data from a region to analyze data and build predictive models and have constructed models and mechanistic analyses with regional characteristics, and this section will summarize some typical regional and model research cases. We summarize the cases in Table 10.

**Table 10.** Validation results in typical case studies.

| Region | Authors | Case Description | Validation Results |
|---|---|---|---|
| Australia | Tran [73] | • Tran developed several deterioration models to evaluate the sewer pipe conditions in the City of Greater Dandenong in Victoria, Australia. Some important influencing factors had been used in these models, such as pipe age, pipe shape, pipe size, and so on.<br>• The most reliable models that Tran identified are the Markov model, Multiple discriminant analysis, Ordered probit, BPNN, and PNN<br>• In this case, the Markov model is used to predict the structural deterioration at the pipe group level, and the other models are used at the pipe group and pipe level. | • As for the pipe group models, the Markov model, BPNN, and PNN passed the goodness-of-fit test, and the Markov model got the lowest chi-square value, showing the best performance in predicting.<br>• For the pipe level models, the best performed model is BPNN because of its total model efficiency for the calibration dataset. |
| USA | Salman [34] | • Salman applied several deterioration models based on inspection data of the city of Cincinnati, USA. The inspection data were evaluated using the PACP procedures.<br>• Several influencing factors had been selected, such as pipe age, pipe material, pipe function, pipe size, pipe depth, and so on.<br>• The selected deterioration models focused on the pipe level: ordinal regression, multinomial logistic regression, and binary logistic regression analysis. | • Necessary model assumptions were not matched so the ordinal regression model cannot be used in this case.<br>• Three condition classes (poor, fail, and good) were tested in the multinomial logistic regression model. The validation result shows that the total model efficiency was moderate but prediction efficiency for class 'fair' is low, so this model was considered to be invalid.<br>• As for the binary logistic regression analysis, two condition classes were applied (good and bad), and the validation result showed a relatively good result: the total model efficiency was 66%, and prediction efficiency for good and bad condition were 78% and 46%. |
| UK | OS Tade [144] | • Totally, 703,156 records of historic sewer structural condition inspection data from a 24,252 km pipeline in Thames Water and other wastewater utilities in the UK had been analyzed.<br>• An improved deterioration model named the Deterministic Deterioration Model (DDM) and inspection frequencies for sewers were developed as a premise for proactive investment in this case. | • In this case, the validation focus was on benchmarking the deterioration model on collapse data.<br>• The validation results indicate the predicted value could be higher than validation result, and that confirms that the deterioration model is valid. |

**Table 10.** *Cont.*

| Region | Authors | Case Description | Validation Results |
|---|---|---|---|
| Germany | Le Gat [99] | • Based on inspection data from the city of Dresden, Germany, Le Gat developed a statistical deterioration model, which is an improved model for non-homogeneous Markov chains. The data were evaluated using the DWA procedures (Germany pipe assessment procedures).<br>• Pipe diameter, installation period, and the type of effluent have been selected for the transition functions. | • The model has been validated using a methodology based on the ability of the models to identify sewers in poor condition.<br>• The validation result shows the model gave a good performance in poor condition. |
| Belgium | Ana [104] | • Ana applied some deterioration models (cohort survival, semi-Markov, logistic regression, Multiple Discriminant Analysis, and PNN) on sewer and inspection data of the city of Leuven and Antwerp, Belgium. In this case, about 1255 samples based on 50 km of sewers were used.<br>• Several influencing factors had been used in this case, such as pipe age, pipe material, pipe function, pipe shape, and so on.<br>• Cohort survival, semi-Markov had been divided into pipe group, and logistic regression, Multiple Discriminant Analysis, and PNN had been selected into pipe level models. | • Pipe group models cannot pass the confusion matrix whereas pipe group models are evaluated using the chi-square goodness-of-fit. The results indicate cohort survival perform better than semi-Markov.<br>• As for the pipe-level models, the efficiency was calculated from the confusion matrices, and the logistic regression and the PNN show good overall prediction quality. |

5.2.2. Validation Result Discussion

In the preceding sections, we have introduced validation methodologies in two dimensions, pipe group and pipe level, and provided examples of application in various regions. We can draw discussions from the preceding cases.

Several deterioration models have been discussed, many of which appear repeatedly (e.g., Markov model, logistic regression, Multiple Discriminant Analysis, and PNN). However, the same model produces different model effects in different cases. The Markov model performs better in most cases, which is attributed to the Markov model's excellent computational potential and the reduction of errors due to the large number of data samples [73,99]. Logistic regression and Multiple Discriminant Analysis have also been tested in a variety of datasets, but have failed miserably. The following factors may contribute to logistic regression's inefficiency: (i) biased distribution of the data set in terms of the number of samples per condition state, and (ii) a lack of data for significant worsening factors [104]. Non-valid statistical assumptions may be a major cause of Multiple Discriminant Analysis's inefficiency [16]. Similarly, the neural network model has proven to be an excellent method for analyzing data in a wide range of applications, but it does not perform well in case studies because it requires a large amount of data, which is typically difficult to obtain in the field of sewer pipe assessment, affecting the model's accuracy [38].

Many conclusions can be summarized [28,96,134]: (i) the quality of the field test data, which is, again, closely related to the selection criteria, influencing factors, and so on, limits the accuracy of validation, (ii) validation results are usually better when analyzing a database with a large amount of data, and (iii) while it is difficult to say which model performs better in general, each model has relative advantages in different application scenarios.

## 6. Summary and Conclusions

The current state of two applications of drainage pipeline condition assessment and deterioration prediction models is reviewed in this paper. Following that, we will summarize and discuss each of these two elements.

### *6.1. Summary and Conclusions of Drainage Pipeline Condition Assessment*

In terms of drainage pipeline condition assessment, we summarize the pipeline construction and maintenance development process from the standpoint of historical development. In Chapter 2, we examine several representative pipeline evaluation manuals and standards, as well as summarize pipeline damage patterns based on these manuals and standards. In Chapter 3, we summarize the main influencing factors used in pipeline condition assessment and analyze their main influencing patterns using a large body of literature.

Table 1 shows that, over time and with the accumulation of a large number of engineering practical experiences, the manuals and standards of each country gradually converge and generally adopt the evaluation ideas of the same category of WRc SRM. However, there is some variation in the classification of pipeline defects used by different countries, making it difficult to combine and analyze pipeline evaluation analysis reports and literature from different countries. On this basis, we have summarized and condensed the manuals and standards of various countries, proposed a set of pipeline defect classifications based on structural and functional defects, and refined and enriched them.

Considering the distribution of the literature, etc., the number of literature materials that use PACP, SRM, and ACCEM is significantly higher than the others. A more advanced pipeline condition assessment system has been formed by the mature system, improved data, and investment in research potential, and the pipe deterioration models established based on the improved database have gradually formed a system.

Similarly, the similarities and differences in influencing factors caused by various evaluation systems are an issue that cannot be overlooked. Drainage pipe condition factors are selected in very different ways across different spans of literature (e.g., chronological span, regional span, research background span, etc.), and even some of the influence factors in many studies reflect very low impact effects in the final results, so refining the mechanistic model of influence factors and targeting the selection of influence factors based on the former study is a good way to improve the model's applicability.

In the selection of influencing factors and the mechanism model analysis, there is still a significant scarcity, such as pipe depth, pipe shape, construction location, groundwater level, and flow rate, and other influencing factors of the mechanism model are still very general: the lack of systematic related research (the reason why possibly being a lack of researchers with underground structure), geotechnical engineering, and other research backgrounds into the specific research. Another possible reason is that pipeline data acquisition and evaluation relies heavily on internal pipeline inspection techniques such as CCTV, and the lack of research variables and data for the overall study of pipe-geotechnical systems makes targeted verification and analysis difficult.

### *6.2. Summary and Conclusions of Deterioration Prediction Models*

The development of deterioration prediction models is undertaken to reduce the loss of human and material resources caused by frequent pipeline inspection and maintenance, as well as to improve the proactiveness of the operation and maintenance process. A large number of models are currently being used in the assessment of drainage pipeline conditions. Models are classified into three types based on their modeling mechanism: physical models, statistical models, and AI models, while models are classified into pipe-group models and pipe level models based on their application.

In terms of modeling mechanisms, a physical model is a pipeline deterioration prediction model based on a large number of assumptions, which has greater application limitations, whereas a statistical model and an AI model are models based on a large number of known data, whose data sources are usually the results of artificial estimation and analysis of pipeline internal inspection techniques such as CCTV. Such data sources are extremely expensive, and it is difficult to obtain such data sources.

So far, there is no literature to prove which model is clearly the best, and the difference in model performance is reflected in the regional variability of pipelines, manuals and standards, and model applicability conditions. Similarly, ambiguity in the mechanism model and confusion in the selection of influencing factors cause errors in the modeling process, reminding us that influencing factors are a pivotal connecting bridge in the subject of this paper, and more attention should be paid to the selection of influencing factors and the mechanism model in future research.

During model validation, we divide the model into pipe group models and pipe level models to gain a better perspective on the problem and obtain the final validation results. The pipes are divided into pipe groups with specific research significance based on their unique regional characteristics in the pipe group model, whereas in the pipe level model, we usually focus only on the pipe itself and ignore the variation characteristics of the pipe as a whole. Model validation can provide theoretical validation as well as practical application of the model, and it determines whether the model has real-world effects. We discovered that the discussion of validation results is relatively lacking and limited after reviewing a large amount of literature. This is due to a lack of pipeline data quality and quantity, which is due to the influence of human evaluation on data quality, resulting in large errors in the data itself, which affects the calculation and prediction of the model itself and the expensive cost of the quantitative aspects of the survey and analysis, which hinders the magnitude and frequency of the data.

## 7. Discussion and Future Perspective

### *7.1. Discussion and Limitations*

Drainage pipeline condition evaluation is a proactive O&M process requiring a large amount of data and adequate feature classification that simultaneously assimilates traditional municipal engineering applications and focuses on professional experience drawn from materials science, geology, geotechnics, fluid mechanics, and other directions to identify influencing factors while giving different interpretations to pipeline condition influencing factors.

Identifying the influencing factors of pipeline condition is key to the success of the evaluation process. Selecting important influencing factors and collecting data in a targeted manner can effectively reduce the investment of human and material resources. At the same time, the importance of the influencing factors also determines the validity and generalization degree of the developed evaluation model. At present, there are few studies that have attempted to explain the mechanism of the influencing factors of pipeline conditions, mostly due to the lack of sufficient data to build an evaluation model with application value.

The rapid development of algorithms and processor upgrades have improved the accuracy and generalization of evaluation models, but the excessive focus on the model itself and neglect of influencing factors and data processing have become important factors that reduce the interpretability of the model. In addition, the implementation of the drainage pipe deterioration and damage evaluation model is still at the stage of theoretical research and is difficult to advance to practical applications, and this has become an important factor limiting the development of the research.

The issues that still need to be addressed are:

1. The lack of investigation of the mechanism of the pipe deterioration and breakage process. The process of pipeline deterioration and breakage is very complex, and

it is difficult to describe the mechanism of pipeline deterioration and breakage by employing a single discipline.
2. Model building is usually limited by the availability of data. Drainage pipeline deterioration and damage prediction models often require a large amount of data to build the model, and the lack of data can lead to problems such as overfitting. A large amount of pipeline data is concentrated in the hands of pipeline operation and maintenance agencies or inspection agencies. The making available of this data would promote the in-depth study and application of the data to increase the possibility of models being used in the active operation and maintenance of pipelines.
3. Existing models are difficult to widely apply. The current model is difficult to build a highly accurate and dynamically descriptive drainage pipe deterioration model because of insufficient data levels, lack of data quality, and insufficient data analysis of time span, and thus it is difficult to put into large-scale practical applications.
4. Drainage pipeline health evaluation systems are difficult to unify. It is difficult to use the models and mechanisms applied in different standards and evaluation systems. Therefore, the promotion of the unification of the evaluation system in regions where pipeline health evaluation systems are relatively mature is recommended.

### *7.2. Future Perspective and Suggestions*

In view of the work that has been carried out so far and the limitations of the study, the following points are suggested:

1. Experts from different research backgrounds should be combined to suggest interdisciplinary research on influencing factors and mechanistic models.
2. The existing pipeline inspection data should be integrated, a database with regional characteristics should be established, and pipeline inspection work under different time spans should be promoted to establish a large number of databases with temporal and spatial dimensions for drainage pipe condition assessment.
3. The quality of pipeline inspection data is a very important issue, and there are already researchers working on the development of an algorithm-based automatic pipeline defect detection system. The joint application of automatic pipeline defect detection and the drainage pipe deterioration prediction model is a very challenging and promising direction.
4. There is an urgent need to summarize and condense manuals and standards from different countries and regions to pave the way for a cross-regional discussion of literature results.

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