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A Deterioration Model for Sewer Pipes Using CCTV and Artificial Intelligence

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Abstract: Sewer pipeline failures pose significant threats to the environment and public health. To tackle these repercussions, many deterioration models have been developed to predict the conditions of sewer pipes, most of which are based on CCTV inspection reports. However, these reports are prone to errors due to their subjective nature and human involvement. More importantly, there are insufficient data to develop prudent deterioration models. To address these shortcomings, this paper aims to develop a CCTV-based deterioration model for sewer pipes using Artificial Intelligence (AI). The AI-based model relies on the integration of an unsupervised, multilinear regression technique and Weibull analysis. Findings derived from the Weibull deterioration curve indicate that the useful service life for concrete and vitrified clay pipes are 79 years and 48 years, respectively. The regression models show that the R^2 value for vitrified clay sewer pipes, concrete sewer pipes, and ductile iron sewer pipes are 71.18%, 71.47%, and 81.51%, respectively, and 73.69% for concrete stormwater pipes. To illustrate the impact of various factors on sewer pipes, sensitivity analyses under different scenarios are conducted. These analyses indicate that pipe diameter has a significant influence on sewer pipe deterioration, with little impact on stormwater pipes. These findings would guide decision makers in identifying critical pipes and taking necessary precautionary measures. Further, this provides a sound basis for prioritizing maintenance actions, which would pave the way for designing sustainable urban drainage systems for cities.

Keywords: machine learning; deterioration models; maintenance; artificial intelligence; robot-based inspection techniques

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1. Introduction

To date, reactive management has been dominantly adopted in dealing with the problem of sewer pipes deterioration [1], with repair and maintenance being carried out at the point of pipe failure. However, this approach is considered unsustainable. An important aspect of effective maintenance of sewer systems includes environmental performance and sustainability [2]. In this regard, Iurchenko et al. [3] argued that sewer pipeline failure in urban regions can pose a wide range of risks to the environment, by affecting the safety of water, soil, air, etc. Several toxic gases are contained in sewers because of the biodegradation of waste in pipelines. The combination of these toxic gases is dangerous to nearby communities [4]. Held et al. [5] noted that sewer pipeline failure results in the infiltration of wastewater into the ground, which ultimately penetrates the groundwater.

This leads to the contamination of the soil and underground water that is meant for drinking. Sewer discharge poses a great contamination risk to nearby water bodies too [6].

With the above in mind, sewer pipes are expected to work efficiently for a period if under normal operating conditions. The deterioration of pipes is caused by different external environmental factors [7–9]. Zuo et al. [10] noted that the lifespan of pipes can be increased through effective maintenance and rehabilitation programs. In order to ascertain the condition of pipes, inspections are carried out. The Closed-Circuit Television (CCTV) inspection method is the most commonly used to assess sewer pipes' deterioration. It involves the use of cameras to record videos and produce footage of the internal surface of the pipeline above the flow line, continuously [11]. Videos and footage are then interpreted by specialists and conclusions are made concerning the conditions of the sewers. Pipelines are evaluated individually and rated according to the degree of recurrence of defects and the severity. Using this rating approach, the operator assigns a score to each pipeline, usually on a five-grade scale [12]. According to Salman and Salem [13], sewer rehabilitation in urban cities is difficult due to the high number of sewer pipelines and limited resources. It is, therefore, important to have an efficient and accurate tool for managing the pipes based on their condition states.

There are several factors that play a role in the deterioration of sewer pipelines. For instance, Salihu et al. [14] noted that age, material, length, size, soil type, water table, and proximity to other utilities are among the factors that affect the performance of sewers and contribute to pipe deterioration. Chughtai and Zayed [15], Chughtai and Zayed [16] argued that physical, functional, and environmental factors affect sewer structural conditions. Examples of these physical factors for pipes are the diameter, age, length, material, and gradient. Functional factors include maintenance and operational approaches for sewer and stormwater pipes. Moreover, there are some environmental factors that affect sewer and stormwater pipes deterioration, including groundwater, waste type, soil type, traffic intensity above the pipe, bedding material proximity to other underground utilities, and frost-related factors [17].

Therefore, accurate data are required for the efficient management of stormwater pipe networks, to assess the pipe network's structural condition [18]. Governments at all levels need to prepare yearly budgets, containing the stormwater network's depreciation value. Thus, a cogent method to evaluating deterioration is to relate it to the storm water pipes' structural depreciation [18]. Standard techniques must be applied to calibrate models using data from the stormwater asset regional database in order to ensure the accuracy of the results. For instance, the Markov model was found to be consistent with the structural data. The diameter characteristics, soil type, construction material, and exposure categorization influence the deterioration process. However, the required deterioration techniques can considerably overestimate the structural deterioration of stormwater pipe networks. For instance, the application of probabilistic neural network (PNN) to model the structural depreciation of stormwater pipes [19]. The PNN model had more accurate predictive power and uses significantly more data input variables than the discriminant model. More significantly, the major for PNN model prediction are complex to explain, implying that, besides accuracy on prediction, model interpretation is another major concern which requires further analysis [19]. The neural network models for deterioration and serviceability condition of buried stormwater pipes were analyzed by Tran et al. [20]. The predictive performance of neural network modelling (NNM) using Bayesian weight computation was more accurate than using the traditional backpropagation and multiple discrimination analysis (MDA) model. The age of pipes and location were the most significant among the analyzed factors. However, the buried depth, soil, and structure were insignificant factors. Thus, it was inferred that a more accurate and reliable data gathering process can facilitate NNM predictive performance and identify significant factors [20].

To capture these factors and their impacts, many mathematical models have emerged, aiming to properly model the deterioration of sewer pipelines [21]. These models include physical models, Artificial Intelligence-based (AI) models, and statistical-based models.

Physical models are concerned with the depiction of physical underlying factors and processes that lead to pipe failures [22]. However, the AI-based models are used in portraying sewer deterioration state and condition rating of pipes [19,23,24]. In this regard, regression has been used by many researchers for determining the probability of failure in pipes [25–29]. For example, a binary logistic regression model was developed by Ariaratnam et al. [25] for the sewer network of Edmonton to predict the likelihood that a sewer pipe is in a deficient state. Likewise, Ahmadi et al. [30], Ahmadi et al. [31] examined how regression-based modelling is useful for planning inspection strategies. On the other hand, statistical-based models are employed to predict sewer pipe deterioration conditions [21,26,27,32,33] and pipe breakages rates [33].

With the above in mind, the deterioration models developed hitherto have not yet proposed a prudent framework for tackling the incompletion of data. That is, in many cities all the influential data related to the constructed drainage networks are not fully provided, due to poor data documentation [1]. Taking steps towards developing a comprehensive deterioration model that can take care of the aforementioned shortcomings is, therefore, needed. Considering this, the followings research questions are formulated:

1. How can a prudent deterioration model be developed based on pipe age and structural grading?
2. How can a predictive-based model be developed when there are inconsistencies with inspection data?

To provide answers to these questions, this study attempted to develop a model for assessing the deterioration of sewer pipes using a theoretical approach to modeling (Weibull analysis) and an independent empirical approach (CCTV, K-means clustering, and multivariate regression).

1.1. Deterioration Models

The major statistical models that have been developed are survival analysis, Markov-chain, regression, and discriminant analysis. Survival analysis and Markov-chain are common types of statistical deterioration models at a network level [18,34–38]. In recent years, several sewer pipe deterioration regression models have emerged, which include linear regression [39], multiple regression [26], logistic regression [24,33,40,41], and multinomial regression [42]. The common premise of these models is that a linear relationship exists between the condition rating of pipes and pipe factors. Various studies have attempted to improve the sewer pipe deterioration models by considering geospatial factors like soil type, soil compaction, existence of trees, fluctuation in groundwater level, and activities above the ground and underground [21,42]. Regression models were successfully used in ascertaining the probability of failure of individual pipes [13,28–30,43–45].

Artificial intelligence-based methods were used in portraying sewer deterioration states (i.e., the condition rating of pipes) [23,24,36,46]. In the prevailing literature, several neural network models for predicting the deterioration of sewer pipelines have been developed [1,24,47–49]. Khan et al. [50] used both Back Propagation Neural Networks (BPNN) and Probabilistic Neural Networks (PNN) for structural condition assessment of sewer pipes. Rajani et al. [51] presented how inspected pipe conditions can be classified as a fuzzy set using the fuzzy set theory. Daher et al. [52] also developed a defect-based condition assessment model using fuzzy. Additionally, the Random Forest method has been used in developing deterioration models. Another artificial intelligence-based model is the Support Vector Machines [35,53–55]. This technique has been adopted in many other studies [24,56–58].

Deterministic models are developed through the grasp of the physical processes of sewer deterioration. Therefore, Marlow et al. [59] noted that empirical deterministic models require matching some forms of linear or nonlinear equations to the observed asset failure. ExtCorr is a deterministic model developed within the Care-S project [60]. It estimates the external corrosion of concrete pipes by evaluating the moisture of the soil, quality of cement used for the pipe, and soil aggressiveness. The WATS model is another example of a "deterministic in-sewer process model" that is used to simulate internal corrosion. Sewer deterioration is a complex challenge that is dependent on a lot of different factors [61]. Despite their variety and advancements, deterministic models are typically too simplistic, making it difficult to show the real deterioration process. The shortage of data required to accurately simulate the deterioration mechanisms reduces their applicability [62].

Prediction of hydraulic deterioration is essential for efficient management of stormwater drainage pipes [63]. Thus, a comparison of hydraulic deterioration models (PNN and Ordered Probit) for stormwater drainage pipes revealed that the ordered probit deterioration model (OPDM) and PNN deterioration model (PNNDM) can be established using the major factors as model inputs and the hydraulic condition as model input. Their analytical performance revealed that the PNNDM was more appropriate for forecasting the hydraulic deterioration and outperformed the OPDM. Many input factors including pipe age and size were significant concerning stormwater pipes' hydraulic deterioration [63]. Modelling the structural deterioration of an urban stormwater drainage pipe network system is essential for understanding the current state of the art in statistical methods [64]. Stormwater collection and transportation structures are undergoing deterioration and aging, making urban centers more vulnerable to their effects, e.g., flooding and collapse.

Stormwater pipe deterioration is considered a complex process which is influenced by many factors. Therefore, predicting when a pipe will collapse or fail is a complex task. Ana and Bauwens [64] suggested that the best technique to predict pipe deterioration is by using a combination of empirical data and probability-based equations to evaluate the structural condition of stormwater pipes throughout their lifespan. Interested readers are referred to a detailed discussion of statistical methods used in forecasting the structural deterioration of urban stormwater drainage system by Ana and Bauwens [64]. Forecasting structural depreciation condition of different stormwater pipes using PNN and multiple logistic regression (MLR) models was attempted by Tran et al. [65]. The depreciation pattern of stormwater pipes is built based on individual pipe and has its own rate of deterioration because of its pipe factors. Thus, Tran et al. [3] used two statistical models (PNN and MLR), which were established to forecast the structural condition of different types of pipes. The PNN model was trained using a genetic algorithm and the PNN model calibrated using the maximum likelihood technique. The CCTV data was used to compare the predictive performance of the two models. The PNN model's result was more suitable for forecasting the structural deterioration of different types of stormwater pipes, compared against the MLR model. Additionally, the application of genetic algorithm enhanced the PNN model's training results better than the trial-and-error technique. Depreciation, deterioration, and serviceability of structural deterioration of stormwater pipes was conducted using a Markov model [66].

The Bayesian methods were used to calibrate the model to the structural condition data from the stormwater asset database. The Markov model was consistent with the data. The pipe diameter categories, soil type, construction material, and exposure classification were major factors influencing the deterioration process [66]. The rational approach to the evaluation of deterioration is to relate it to structural deterioration. However, the emphasis on structural condition is rather artificial and does not address the essential issues concerning stormwater pipe assets' management [66]. Hence, it is suggested that the level of service offered by the pipe relies on its position in the network and on factors lessening its original hydraulic capacity including sedimentation, tree roots, and collection of debris. The defects identified in serviceability rating from SEWART surveys can be apportioned loss coefficients. Using these coefficients in hydraulic model of the pipe enables the assessment of surcharge frequency and hence the pipe's serviceability. Thus, a combination of both serviceability and structural conditions must be considered to determine a strategy for stormwater pipe management.

Therefore, classifying the structural condition of stormwater deteriorating pipes using support vector machine (SVM) was performed. Tran and Ng [67] attempted to enhance the prediction or classification of structural condition of different types of storm water pipes.

This type of predictive data can be used to rank pipes for maintenance and subsequent inspection actions and, therefore, support water companies in implementing their proactive management strategies [67]. Thus, a SVM was established, verified, and compared to the backpropagation neural network (BPNN) model which has been previously used in the literature. The established model was used for a case study using a sample of CCTV examined pipes and analogous pipe factors. Concerning accurate prediction of structural condition of different types of stormwater pipes, the SVM model significantly overtook the BPNN in the train dataset and marginally in the test dataset. Likewise, many benefits of the SVM model were found in relation to the BPNN model [67].

Therefore, a sustainable financing strategy for storm water asset management using a system dynamics model was proposed [68]. The model comprised qualitative assessment that utilizes casual loop diagrams to provide a theoretical framework presentation and statistical formulation for qualitative evaluation. The model was utilized to search the prospect for introducing stormwater fees in urban areas [68]. Further the model was helpful in strategic infrastructure management decision making and was utilized to establish arguments for executing proactive infrastructure management programs [68]. The Weibull analysis, extrapolations and implications for assessing the condition of cast iron water mains was considered [69]. Results indicated that the predicted strengths of the pipes are close to the lower end of the measured distribution of pipe strengths. Consequently, the model prediction of pipe strengths is near to the lower end of the measured distribution of pipe strength. Thus, Belmonte et al. [69]'s study suggested that Weibull analysis is an effective tool to assess the strength distribution of detached-from-cast-iron water pipes and, thus, has the prospect of contributing in the evaluation of infrastructure condition.

1.2. Weibull Analysis

Weibull analysis is a popular method of analysis used for predicting failure and malfunctions [70]. Mailhot et al. [71] used the Weibull distribution to determine the time to first pipe break, i.e., failure and subsequent breaks. Moreover, Duchesne et al. [36] applied the Weibull distribution to model waiting times in each deterioration state. Vladeanu and Koo [72] developed a Weibull model that focused on the percentage probability of failure for cast iron pipes. Lastly, Laakso et al. [73] used the Weibull regression to ascertain the share of pipes in good condition based on the dataset used for the study.

1.3. Point of Departure

Based on the reviewed literature, this research has identified the following gaps: Current existing deterioration models require a high volume of inspection data. In some instances, these data are not readily available. The need to develop a model with a limited database is critical to provide a guide for professionals in charge of managing and maintaining the pipes. This acknowledges the importance of the first objective of this study to develop a Weibull deterioration curve for different pipe materials using the pipe age and structural grading of the pipes. The subjectivity of CCTV inspection reports creates uncertainty about their accuracy. This creates a need for carrying out unsupervised learning on data for different factors (that cause sewer deterioration) and comparing the results of unsupervised learning with actual data to ascertain the percentage of similarity. Furthermore, unsupervised learning assists in identifying hidden patterns in the deterioration process that might not be identified during a physical inspection, as the second objective of this paper.

2. Research Methods

The method adopted in this study follows a three-phased procedure. Phase A is concerned with a literature review, data collection, and data sorting and cleaning, while Phases B and C are, respectively, related to the development of the Weibull Deterioration curve and an unsupervised-based, multilinear regression model, as illustrated in Figure 1.

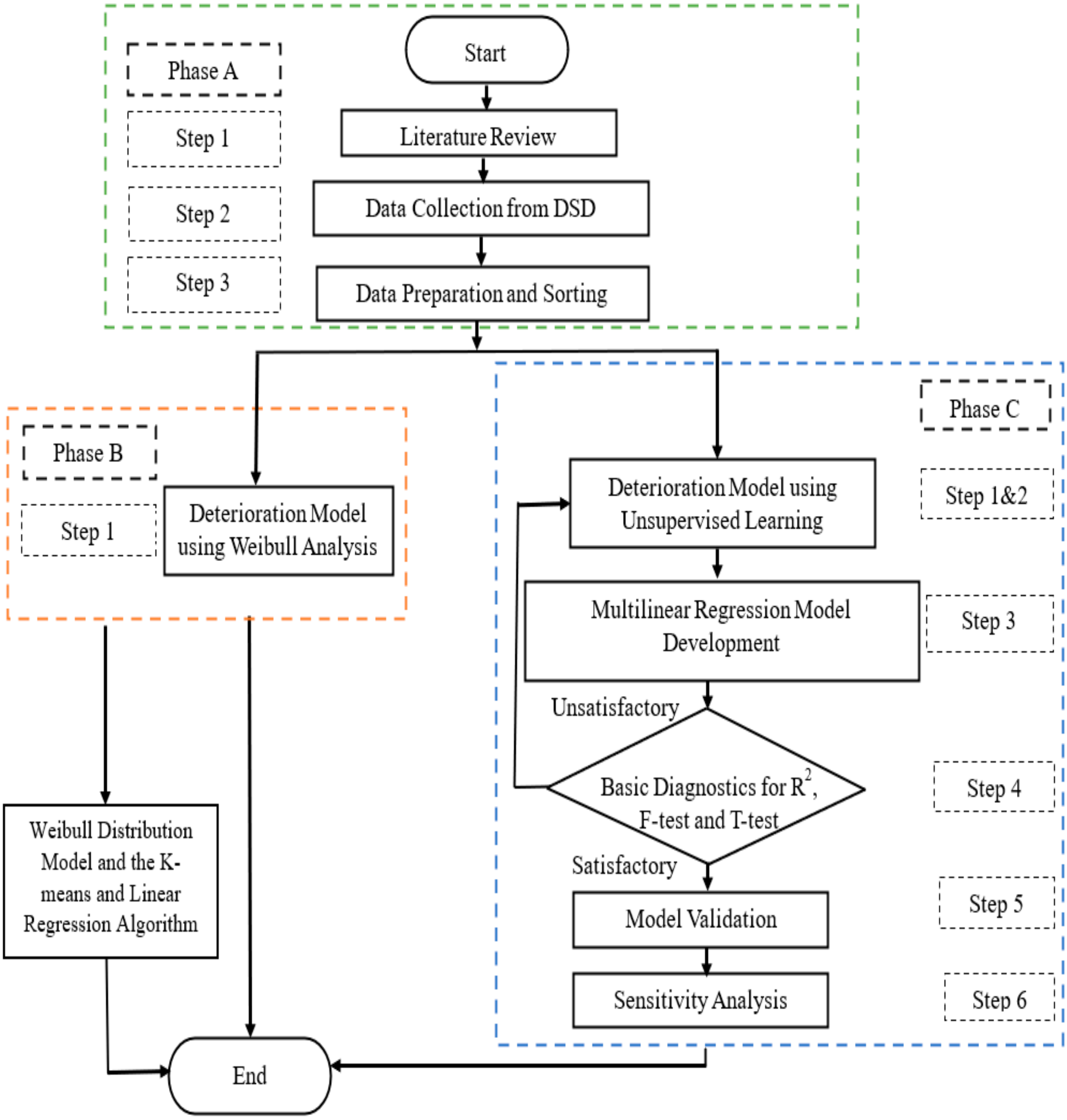


Figure 1. Research methodology.

2.1. Phase A

Step 1: Relevant literature are reviewed. These cover subtopics of existing deterioration models and Weibull analysis.

Step 2: In developing the model, CCTV inspection data were collected from the drainage service department in Hong Kong. The data coverage was for Tsim Sha Tsui (TST). The data comprised details of the pipe length, pipe material, pipe shape, pipe diameter, and the structural grading ICG. The age of the oldest pipe in the data collected was 72 years. A total of 1407 sewer pipes and 1448 stormwater pipes were used for model development.

Step 3: The data were sorted and cleaned by removing pipe units that did not have the complete data. Thee comprised pipes without records for age, length, and diameter. Furthermore, pipes without structural grading ICG were not considered.

2.2. Phase B

Step 1: Weibull analysis was carried out to develop a Weibull deterioration curve based on the pipe age. This model was developed based on age and structural grading ICG. It provides an answer to the first research question. The expected service life for the different pipe materials was ascertained, the useful service life based on the structural grading was determined and the Weibull formula was applied to get the deterioration curve [70].

The Weibull probability distribution function is presented in Equation (1):

$$f(t) = \frac{\delta}{\tau}\left(\frac{t-\alpha}{\tau}\right)^{\delta-1} \times ^{-\left(\frac{t-\alpha}{\tau}\right)^{\delta}} \tag{1}$$

where, α = location parameter, τ = scale parameter, δ = shape parameter, t = time.

The Weibull cumulative distribution function is as shown in Equation (2):

$$F(t) = 1 - e^{-\left(\frac{t-\alpha}{\tau}\right)^{\delta}} \tag{2}$$

Thus, the Weibull reliability function is represented as Equation (3):

$$R(t) = 1 - F(t) = e^{-\left(\frac{t-\alpha}{\tau}\right)^{\delta}} \tag{3}$$

The deterioration curve has the same shape as Weibull reliability curve; this is shown as Equation (4) below:

$$P(t) = \alpha \times e^{-\left(\frac{t}{\tau}\right)^{\delta}} \tag{4}$$

where;

P (t) = Performance index at time *(t)*,

τ = service life

Estimating the parameters of the Weibull distribution can be either graphically, by means of probability plotting paper, or analytically, by using the least squares or maximum likelihood [74].

2.3. Phase C

Step 1: Unsupervised learning is the process of using automatic data analysis techniques to unravel hidden relationships amongst variables in a dataset [75]. It enables researchers to analyze data from different angles. Clustering is the vital feature of data mining. It is a method of grouping data based on their similarity measures. Data in one cluster are similar to each other and relate. Clustering is an unsupervised learning method [76]. It uses two algorithms: the hierarchical algorithm, which entails dividing a dataset into smaller subset in a hierarchical pattern; and the partition algorithm, which entails dividing a dataset into a desired number of sets in a single step. In this paper the partition algorithm was adopted for the data using K-means clustering. K-means clustering is an unsupervised learning technique that uses the partition algorithm. It uses an iterative approach, which is widely used because of the accuracy of its results and the simplicity of use [77].

Unsupervised learning based on K-means clustering using RapidMiner software version 9.9 was carried out. This is to answer the second research question. In carrying out unsupervised learning, RapidMiner software was selected and K-means clustering was used. The data were imported into the software after which the data was normalized. The input data consists of three variables which are age, diameter, and length. The K-means clustering operator was selected for the clustering. The value of K was set at 5. This is because the structural grade ICG of the pipes is between 1 and 5. Consequently, unsupervised learning was needed to produce five clusters of 1 to 5. The output of the unsupervised learning contained the three variables and the new clusters.

Step 2: The result of the clustering was related to the actual data. It had an average similarity percentage of 89%. The clustering result was then used to carry out a multilinear regression analysis using the factors pipe diameter, pipe age, and pipe length as the independent variables and the structural grade ICG as the dependent variable. This answered the third research question.

Step 3: The multilinear regression model was developed using Minitab statistical software (version 19). Firstly, the best subset analysis was done to ascertain the factors to be considered in the model and then the main analysis was carried out. The factors considered in the model included age, length, and diameter which are the independent variables, and the structural grading ICG which is the dependent variable. Regression equations were generated, and other statistical tables were generated as seen in Section 3.2.

Step 4: Once the model has been developed, there is a need to ascertain how adequate the model is. This is achieved by critically analyzing the coefficient of multiple determination, F test for the regression relation, and t-test for each of the regression parameters [78].

Step 5: The developed model was validated by plotting the actual structural grade ICG with the predicted structural grade ICG. Additionally, the mean and standard deviation of the actual ICG and predicted ICG were calculated, as suggested by Anderson and Davenport [78].

Step 6: Furthermore, sensitivity analysis for the data was conducted for different pipe types and materials. The sensitivity analysis considered the changes in the ICG at different diameters, including age and length. Sensitivity analysis was used to ascertain how individual factors in the model can impact the deterioration process under different conditions.

3. Findings and Discussion

3.1. Deterioration Model Using Weibull Analysis

The Weibull probability distribution function was defined according to Equation (4), which was applied to generate the Weibull deterioration curve as shown in Figure 2.

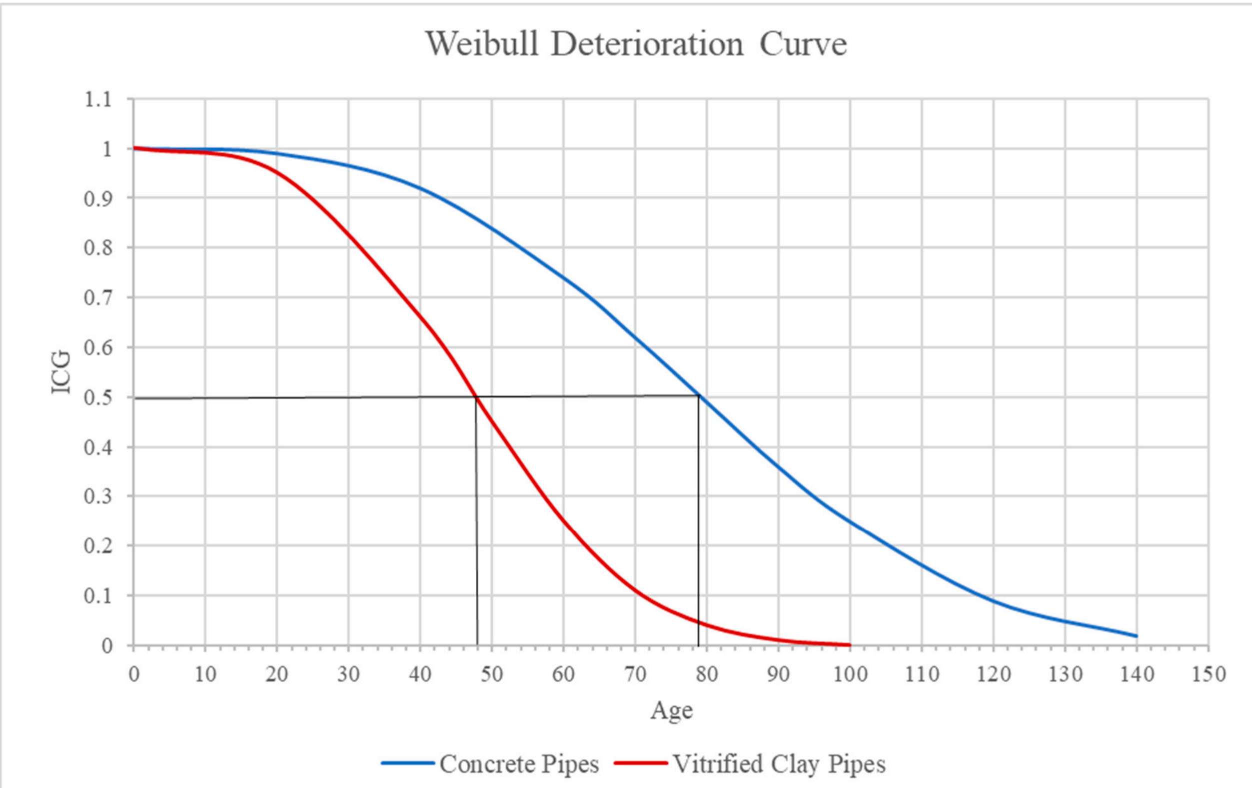


Figure 2. Using an expected service life of 100 years for concrete pipes and 60 years for vitrified clay pipes.

The deterioration curve for sewer pipes was generated based on the conditions defined in Equations (5) to (7), as follows.

1. The newly installed pipes at t = 0 has an ICG of 0, which can be expressed as 1 on a scale from 0 to 1:

$$\begin{gathered} 1 = \alpha \times e^{-\left(\frac{0}{\tau}\right)^{\delta}} \\ 1 = \alpha \end{gathered} \tag{5}$$

2. ICG = 5 at the end of the lifetime of the pipe, while ICG = 2 (critical performance index), which is presented as 0.25 on a scale from 0 to 1 and it represents the end of the useful service life (t):

$$0.25 = 1 \times e^{-\left(\frac{100}{\tau}\right)^{\delta}}, \text{ then}$$

$$\ln(0.25) = \ln(1) - \left(\frac{100}{\tau}\right)^{\delta}$$

And finally:

$$\tau = \frac{100}{(-In(0.25))^{1/\delta}} = 89.68 \quad \text{for concrete pipes} \tag{6}$$

$$\tau = \frac{60}{(-In(0.25))^{1/\delta}} = 53.81 \quad \text{for vitrified clay pipes}$$

3. The shape parameter δ = 3. 3 is chosen because it gives a better curve shape compared to 1, 2,3, 4, etc.

Therefore, by substituting Equations (5) and (6) into Equation (4), the updated deterioration curve can be defined as Equation (7).

$$P(t) = 1 \times e^{-\left(\frac{t}{\tau}\right)^{3}} \tag{7}$$

The deterioration curve shows that ICG 0 to 0.5 is the equivalent of ICG 4 to 2; the pipe is in its useful service life. For concrete, the useful service life of the pipes is 79 years, while that of vitrified clay pipes is 48 years. As the ICG drops from 0.5 or 2 the pipes are then getting to their critical point, with a higher deterioration rate and the likelihood of failure. This implies that more frequent maintenance should be carried out on pipes at this point to improve their functionality.

3.2. Deterioration Models Using Unsupervised K-Means and Multilinear Regression

To develop a multilinear regression model, unsupervised learning of the data was first performed using K-means clustering, based on Equation (8). In carrying out unsupervised learning, RapidMiner software and K-means clustering were used. The data were normalized and imported into the software. The input data consisted of three variables: Age, Diameter, and Length. The K-means clustering operator was selected for the clustering. The value of K was set at 5. This is because the structural grade ICG of the pipes is between 0 to 4. Unsupervised learning was needed to produce five clusters of 0 to 4. The cluster visualization is shown in Figure 3.

$$J = \sum_{j=1}^{k}\sum_{i=1}^{n}\left\| x_i^{(j)} - c_j \right\|^2 \tag{8}$$

where J is the objective function, while k, n, x_i, c_j, and $\left\| x_i^{(j)} - c_j \right\|$ are, respectively, the number of clusters, the number of cases, the ith case, the centroid for jth cluster, and the distance function.

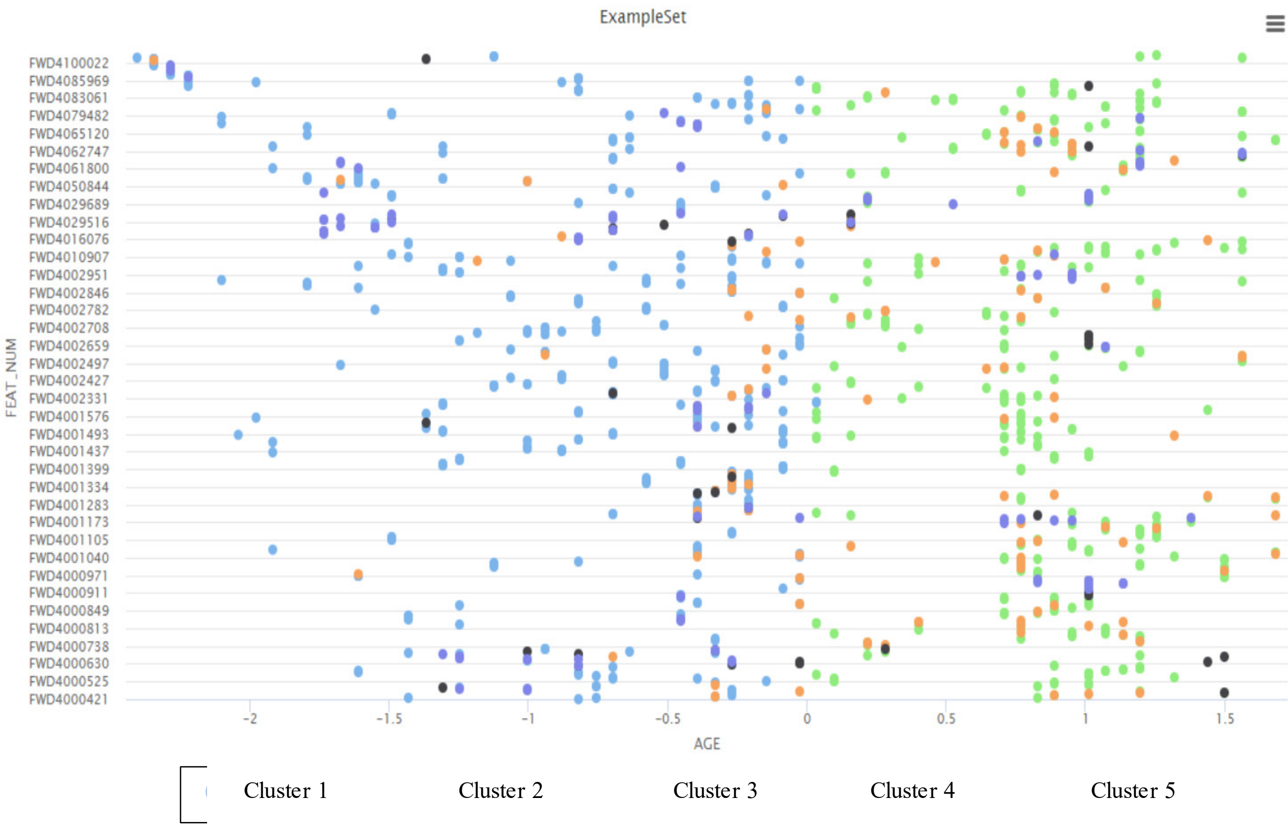


Figure 3. Visualization of clusters.

K-means Algorithm:

1. Clusters the data into k groups where k is predefined.
4. Select k points at random as cluster centers.
5. Assign objects to their closest cluster center according to the *Euclidean distance* function.
6. Calculate the centroid or mean of all objects in each cluster.
7. Repeat steps 2, 3, and 4 until the same points are assigned to each cluster in consecutive rounds.

It comprised different types of pipes: vitrified clay sewer pipes, concrete sewer pipes, ductile iron sewer pipes, concrete stormwater pipes, and ductile iron storm water pipes. Assessing the CCTV-based deterioration patterns of sewer pipe is motivated by the need to pay keen attention to the sewers to avert sewer failure [79]. A sustainable and smart drainage system is largely reliant on the condition of existing sewer pipelines' infrastructure in urban networks. Different factors can cause deterioration of sewer systems; although these factors are well established, the degree of impact each factor has on the sewer deterioration process is not fully and explicitly defined [79]. Hence, this study has attempted to develop a model for sewer pipes using CCTV and Artificial Intelligence. The output of the unsupervised learning contained the three variables and the new clusters. This was related to the actual dataset to ascertain the accuracy of the inspection results, as tabulated in Table 1.

Table 1. Similarity percentage of unsupervised model result with the actual data.

Pipe Type	Percentage of Similarity with Actual Data
Vitrified clay sewer pipes	88%
Concrete sewer pipes	79%
Ductile iron sewer pipes	93%
Concrete stormwater pipes	90%
Ductile iron storm water pipes	95%

The similarity percentage (i.e., in comparison with actual data) indicates that the result of unsupervised model does not have a large deviation from the actual data. Current results agreed with the existing literature [80]. Therefore, the model developed using the clustering result is a satisfactory representation of the actual data [81].

Minitab version 19 was used in building the regression models. The result of the analysis generated a regression equation and other statistical test results, as illustrated in Tables 2–5 for different pipe types and materials. Table 2 presents the regression analysis of vitrified clay sewer pipe comprising: Coefficient (Coef), Standard Error Coefficient (SE Coef), the calculated difference relative to the variation in data (*T*-value), probability value (*p*-value), variance inflation factor (VIF), R-Square(R-Sq), Adjusted R-Square R-sq(adj), Predicted R-Square R-sq(pred), The variance between the means (*F*-value), Degree of freedom (DF), and adjusted mean square (Adj MS). The VIF is an outline of a post-hoc method which estimates the VIF from the standardized regression coefficient and semi partial correlation. Thus, it can be estimated from commonly reported regression results [82].

Table 2. Regression analysis of vitrified clay sewer pipe.

Term	Coef	SE Coef	*T*-Value	*p*-Value	VIF
Constant	1.4399	0.0193	74.53	0.000	
Diameter (m)	0.7802	0.0213	36.62	0.000	1.22
AGE (year)	−0.6915	0.0194	−35.62	0.000	1.01
Length (m)	0.0696	0.0214	3.25	0.001	1.22
Model Summary					
S	R-sq	R-sq(adj)	R-sq(pred)		
0.679996	71.18%	71.11%	70.94%		
Analysis of Variance					
Source	DF	Adj SS	Adj MS	*F*-Value	*p*-Value
Regression	3	1410.21	470.071	1016.60	0.000
Diameter (m)	1	620.12	620.125	1341.12	0.000
AGE (year)	1	586.57	586.571	1268.55	0.000
Length (m)	1	4.90	4.895	10.59	0.001
Error	1235	571.06	0.462		
Lack-of-Fit	1227	571.06	0.465	*	*
Pure Error	8	0.00	0.000		
Total	1238	1981.27			

* Note: Lack of fit for the *p*-value.

Table 3. Regression Analysis of Concrete sewer pipe.

Term	Coef	SE Coef	*T*-Value	*p*-Value	VIF
Constant	1.8239	0.0716	25.47	0.000	
Diameter (m)	0.4233	0.0784	5.40	0.000	1.19
AGE (year)	−1.3519	0.0723	−18.70	0.000	1.01
Length (m)	0.0599	0.0786	0.76	0.447	1.20

Table 3. *Cont.*

Term	**Coef**	**SE Coef**	***T*-Value**	***p*-Value**	**VIF**
Model Summary					
S	R-sq		R-sq(adj)	R-sq(pred)	
0.903053	71.47%		70.92%	69.58%	
Analysis of Variance					
Source	DF	Adj SS	Adj MS	*F*-Value	*p*-Value
Regression	3	316.666	105.555	129.44	0.000
Diameter (m)	1	23.781	23.781	29.16	0.000
AGE (year)	1	285.156	285.156	349.67	0.000
Length (m)	1	0.474	0.474	0.58	0.447
Error	155	126.403	0.816		
Total	158	443.069			

Table 4. Regression Analysis of Ductile iron sewer pipe.

Term	**Coef**	**SE Coef**	***T*-Value**	***p*-Value**	**VIF**
Constant	2.067	0.174	11.89	0.000	
Diameter (m)	−0.778	0.242	−3.22	0.008	1.80
AGE (year)	0.461	0.197	2.33	0.040	1.20
Length (m)	−0.345	0.224	−1.54	0.152	1.55
Model Summary					
S	R-sq		R-sq(adj)	R-sq(pred)	
0.672920	81.51%		76.46%	70.20%	
Analysis of Variance					
Source	DF	Adj SS	Adj MS	*F*-Value	*p*-Value
Regression	3	21.952	7.3174	16.16	0.000
Diameter (m)	1	4.694	4.6945	10.37	0.008
AGE (year)	1	2.467	2.4673	5.45	0.040
Length (m)	1	1.071	1.0706	2.36	0.152
Error	11	4.981	0.4528		
Total	14	26.933			

Table 5. Regression Analysis of Concrete Stormwater pipe.

Term	**Coef**	**SE Coef**	***T*-Value**	***p*-Value**	**VIF**
Constant	1.1298	0.0149	75.59	0.000	
Diameter (m)	0.7252	0.0157	46.31	0.000	1.10
AGE (year)	0.3100	0.0150	20.70	0.000	1.00
Length (m)	0.3820	0.0156	24.43	0.000	1.09
Model Summary					
S	R-sq		R-sq(adj)	R-sq(pred)	
0.568732	73.69%		73.64%	73.53%	
Analysis of Variance					
Source	DF	Adj SS	Adj MS	*F*-Value	*p*-Value
Regression	3	1308.52	436.174	1348.48	0.000
Diameter (m)	1	693.56	693.556	2144.21	0.000
AGE (year)	1	138.54	138.538	428.31	0.000
Length (m)	1	193.11	193.108	597.02	0.000
Error	1444	467.07	0.323		
Lack-of-Fit	1441	467.07	0.324	*	*
Pure Error	3	0.00	0.000		
Total	1447	1775.59			

* Note: Lack of fit for the *p*-value.

The values of R^2 and R^2 (adjusted) for vitrified clay sewer pipes are to be 71.18% and 71.11%, respectively. It indicates that the model fitted the data. Similarly, the values R2 and

R2 (adjusted) for concrete sewer pipes were 71.47% and 70.92%. The ductile iron sewer pipes have a higher R^2 and R^2 (adjusted) value of 81.51% and 76.46% when compared to vitrified clay and concrete sewer pipes. It indicates that the model has a better fit. Furthermore, the concrete stormwater pipe had an R^2 and R^2 (adjusted) value of 73.69% and 73.64%. In general, the models showed good fit. R^2 shows that the predictors explain a certain percentage of the variance in the structural grade ICG, while the R^2 adjusted accounts for the number of predictors in the model.

Additionally, a hypothesis test needs to be done for the F test to determine the P(F) of the entire model. The null hypothesis (H_0) assumes that all regression coefficients are equal to zero. The alternate hypothesis (H_a) assumes that not all of them are equal to zero. From the results, the *p*-value in the analysis of variance table is 0.000 for all material types. It implied that the null hypothesis is rejected, inferring that the model is significant—at a significance level of 0.05 hence—and at least one coefficient in the regression is not zero.

The next step was to test if all predictors are significantly related to the response variable. The *p*-values for all the factors for vitrified clay sewer pipes were significantly related to the response variable ICG at a significance level of 0.05. For concrete sewer pipes the factor length had a *p*-value of 0.447. This shows that it is not significantly related to the response variable at a significance level of 0.05. This is also seen in a ductile iron sewer pipe. The factor length has a *p*-value of 0.152. Furthermore, for the concrete stormwater pipes, all the factors excluding the length factor are significantly related to the response variable at a significance level of 0.05.

The regression model was developed for the different pipe types and pipe materials. The regression equations for the different categories are presented below.

Vitrified clay sewer pipes ICG = 1.4399 + 0.7802 Diameter − 0.6915 Age + 0.0696 Length.

Concrete sewer pipes ICG = 1.8239 + 0.4233 Diameter − 1.3519 Age + 0.0599 Length.

Ductile Iron Sewer pipes ICG = 2.067 − 0.778 Diameter + 0.461 Age − 0.345 Length.

Concrete Stormwater pipes ICG = 1.1298 + 0.7252 Diameter + 0.3100 Age + 0.3820 Length.

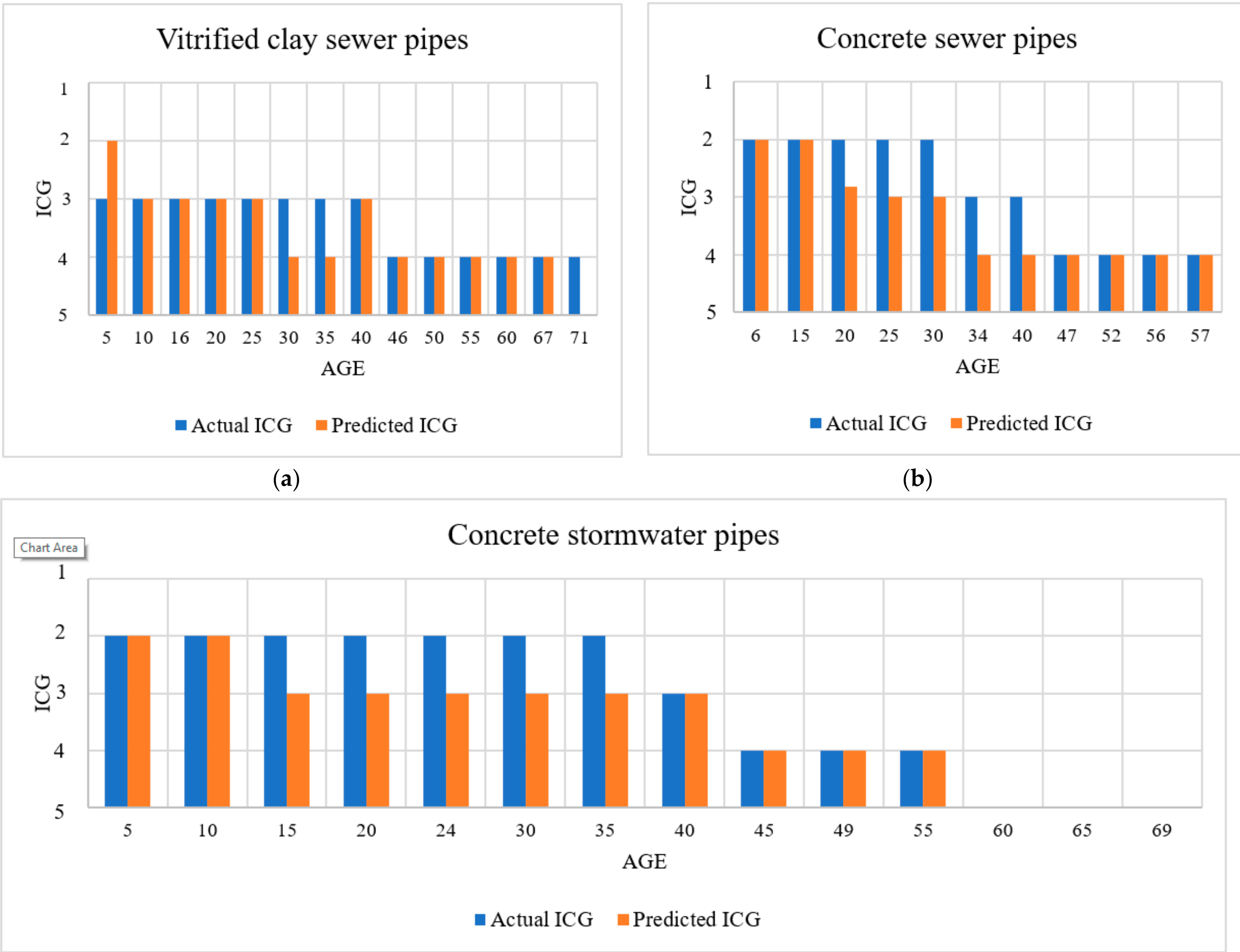
3.3. Model Validation

The model was validated by comparing actual ICG values with the predicted ICG values generated with the regression equation. A graphical representation of the actual ICG and the predicted ICG was plotted. The plot shows that the predicted ICG still falls within the accepted limit of the actual ICG. There was no large variance between the two, indicating that validation results are satisfactory. The plots for the different pipe type and material are seen in Figure 4.

A descriptive analysis table of the validation is shown in Table 6. The result indicates that the mean and standard deviation of the actual ICG and predicted ICG are close to each other with little variation. Therefore, it shows that the model results are satisfactory.

Table 6. Descriptive statistics for model validation.

Pipe Type	Descriptive Statistics			
	Mean		Standard Deviation	
	Actual	Predicted	Actual	Predicted
Vitrified Clay Sewer pipes	2	1	0.51	0.74
Concrete Sewer pipes	3	2	1.42	1.62
Concrete Stormwater pipes	3	3	1.31	1.02



(**c**)

Figure 4. Actual ICG and predicted ICG for different pipe types and materials: (**a**) Vitrified clay sewer pipes, (**b**) Concrete sewer pipes, and (**c**) Concrete stormwater pipes.

3.4. Sensitivity Analysis

Sensitivity analyses helped to ascertain how different values of an independent variable impact a dependent variable based on a given set of assumptions. Sensitivity analysis was, therefore, conducted for observing the impacts of defined variables on the ICGs, as explained below.

The regression equation generated from the regression analysis was used to develop a scatter plot for the pipes at different diameters and age ranges. For vitrified clay sewer pipes and concrete sewer pipes, it was discovered that the diameter of pipes has a significant role to play in pipe deterioration. Pipes with smaller diameter deteriorate faster than pipes with larger diameter. This observation echoes the findings of previous studies [18]. As can be seen in Figure 5a,b, this is exponentially (Expon) ductile in observed for the ductile iron sewer pipes—shown in Figure 5c. "As can be seen in Figure 5a–c, the ductile iron follows an of an exponential trend".

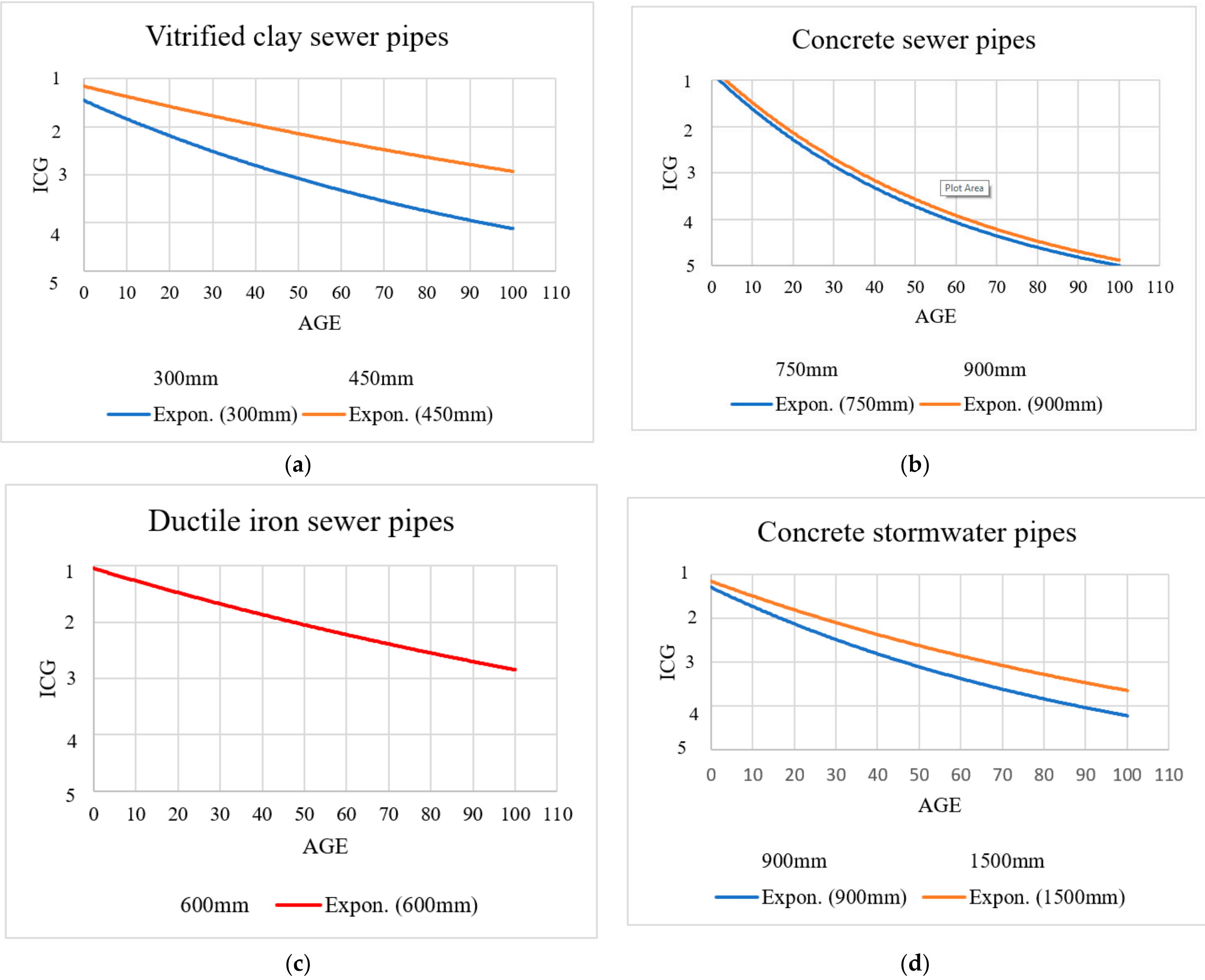


Figure 5. Sensitivity analysis. (**a**) Vitrified clay sewer pipes. (**b**) Concrete sewer pipes. (**c**) Ductile iron sewer pipes. (**d**) Concrete stormwater pipes.

Furthermore, sensitivity analysis was also carried out for concrete stormwater pipes. The scatter plots indicate that the diameter of pipes does not have a significance effect on the deterioration process of stormwater pipes, since there is a severe impact for a diameter increase from 900 to 1500 mm, as seen in Figure 5d.

3.5. Model Summary

The deterioration modelling was established based on Weibull distribution, to construct a system based on the analyzed models of pipes deterioration assessment. The model did not consider the entire data, rather the structural condition scale ICG and the pipe age were factored in. Moreover, regression analysis was based on more factors and the result of unsupervised learning. The Weibull analysis indicated that concrete and vitrified clay pipes reach their useful service life at the age of 79 and 48 years, respectively—their expected service life are 100 and 60 years. Therefore, attention should be paid to pipes within that age range in terms of maintenance.

The sensitivity analysis result shows that the diameter of sewer pipes has a significant influence on the deterioration process, whereas for stormwater pipes, the diameter has little impact. For all pipe types and materials, the ICG of the pipes reduces with age. It, therefore, means that the age of the pipe is also significant to the deterioration process.

From the result, the pipe length has little or no impact on the deterioration process. Using large-diameter pipes for sewers can reduce the deterioration rate and improve the service life of these pipes.

Based on the comparison between the Weibull analysis result and the regression result, it was noted that Weibull only predicts using time, which in this case is the pipe age. Therefore, it can be relied upon as a useful prediction guide when there are insufficient data to develop a more detailed model. In other words, it is a good approach when the expected service life of the pipes and few inspection details with its structural grading are known. Nonetheless, the regression model considered other factors such as length and diameter. The regression model can, therefore, help in predicting the deterioration of pipes with a particular diameter, length, and age at any point in time. When values are submitted into the model it can give the structural class of the pipe at that point in time or in the future. This serves as a useful guide for prioritizing when preparing for maintenance. Therefore, this study's model results can be used to construct a system-based framework for assessing pipes deterioration.

4. Practical Implications

The model developed in this research will be beneficial for professionals in charge of sewer infrastructure in several ways:

1. Having an understanding of the useful service life of the various pipe materials will help in making decisions on the best material to use while designing new sewer lines and replacing old ones.
2. The Weibull deterioration curve will help professionals when planning for maintenance. The need to prioritize pipes that have exceeded their useful service life and the frequency of maintenance to be carried out on such pipes will be well planned. This will improve the lifespan of the pipes.
3. The validation of CCTV inspection results through unsupervised learning will aid professionals to better understand the deterioration patterns given certain conditions and factors. Also, it helps them to ascertain the level of accuracy of inspection reports.
4. The multilinear regression model developed in this study will be used in predicting the future condition state of pipes and when it is likely to fail. This will help in cost saving as measures are put in place to avoid such failure.
5. One of the major impacts of sewer deterioration and failure is on the environment. This is because it can lead to the contamination of soil, drinking water sources, beaches, etc., thereby posing a risk to the health of the populace. The predictive model developed in this study would preclude such risks as a more proactive method of management and maintenance.

Limitation and Future Works

Some limitations are to be acknowledged. That is, drawing the Weibull curve for ductile iron could add value to the study. That was not possible due to a lack of sufficient data, which remains to be addressed in future studies on the topic.

Besides, the developed model does not consider the impact of traffic on pipes; therefore, it cannot be used for any pipes buried under highways. In addition, the developed model only considered three pipe material types which are vitrified clay, concrete, and ductile iron. Future studies should consider more external factors such as high surface pressure, poor pipe structure, human error, variation in temperature, and digging. Besides, environmental stressors such as earthquakes and tremors, etc., that cause sewer pipeline deterioration should be identified, and their impacts need to be further analyzed. Quite a good number of external factors affect the sewer system directly or indirectly. Therefore, it is important to ascertain to what extent these factors contribute to deterioration and how they can be minimized.

5. Conclusions

In this paper, deterioration models for sewer pipes and stormwater pipes were developed for different pipe materials which are concrete, vitrified clay, and ductile iron. The models were developed using multilinear regression analysis and Weibull analysis. The deterioration prediction was based on the Internal Condition grade ICG of 0 to 4. The conclusions drawn from the models developed offer novelty in several ways.

1. Use of Weibull deterioration curve for concrete and vitrified clay pipes based on the pipe age and structural grading. It is a good analysis tool for modeling deterioration when there is not enough data to develop a more detailed model. There is a need to develop a Weibull-based model that takes into account the impact of both pipe age and overall structural grade, i.e., Internal Condition Grade (ICG) of pipe.
2. Utilize unsupervised-based learning of CCTV inspection data using K-means clustering. Most CCTV inspection reports are done based on the inspector's observation and there is often a likelihood to experience human error. Thus, the use of unsupervised learning can overcome such rampant concern, since it identifies patterns and relationships in an unlabeled dataset where insufficient data are provided. With the help of unsupervised learning, the accuracy of these reports can be validated and ascertained, achieving a more reliable model.
3. The results produced from this study give managers a good basis to make decisions and avert the risk that sewer failure would have on the environment.

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