Intelligent Approaches for Predicting Failure of Water Mains

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Abstract: Water mains are indispensable infrastructures in many countries around the world. Several factors may be responsible for the failure of these essential pipelines that negatively impact their integrity and service life. The purpose of this study is to propose models that can predict the average time to failure of water mains by using intelligent approaches, including artificial neural network (ANN), ridge regression (l_2), and ensemble decision tree (EDT) models. The developed models were trained by using collected data from Quebec City water mains, including records of the possible factors, such as the materials, length, and diameter of pipes, that contributed to the failure. The ensemble learning model was applied by using a boosting technique to improve the performance of the decision tree model. All models, however, were able to predict reasonably the failure of water mains. A global sensitivity analysis (GSA) was then conducted to test the robustness of the model and to show clearly the relationship between the input and output of the model. The GSA results show that gray cast iron (CI), hyprescon/concrete (Hy), and ductile iron with lining (DIL) are the most vulnerable materials for the model output. The results also indicate that the failure of water mains mostly depends on pipe material and length. It is hoped that this study will help decision makers to avoid unexpected water main failure. **DOI: 10.1061/(ASCE)PS.1949-1204.0000485.**

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Introduction

Water mains are crucial infrastructures to cities around the world, and their failure can lead to significant economic, environmental, and social losses (Ana and Bauwens 2010). Water mains are expected to have a service life of between 50 and 100 years (Li et al. 2013; Ormsby 2009). More than 300 breaks of large water utilities could occur in a year that could require urgent repair or replacement. The failure of both small and large diameters of water mains could cost millions of dollars for replacement and damage mitigation resulting from the flooding and repair of average roads (Makar et al. 2001).

The deterioration of water mains can be categorized into two types: structural and inner surface deterioration (Kleiner and Rajani 2001). Structural deterioration leads to the diminishing of the ability and resilience of water mains to carry loads (Kleiner and Rajani 2001). The deterioration of the inner surfaces of pipes may result in the degradation of water quality, the diminishing of the hydraulic capacity, and the reduction in the ability of the pipes to withstand internal corrosion. Both types of deteriorations can contribute to the failure of water distribution networks (Kleiner and Rajani 2001).

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Ductile iron, cast iron (CI), asbestos cement, and polyvinyl chloride (PVC) are among the popular materials used in pipelines. Gray CI is commonly used as pipe material for water mains in North America (Makar et al. 2001; Sipos 2010), covering about 50% of the total installed water mains (Kleiner and Rajani 2001). Whereas 11% of the water mains are made of PVC in North America (Rajani and Kleiner 2001). Kettler and Goulter (1985) found that the failure rate of water mains made of asbestos cement and CI pipes increases with time. A significant relation was also found between pipe diameter and the number of breaks (Christodoulou 2011; Kettler and Goulter 1985; Yamijala et al. 2009).

According to a water infrastructure report card published by ASCE in 2017, the water systems in the US have attained an overall grade of D. This means that the water network is operating below standards and is, furthermore, in poor to fair condition. Over two trillion gallons of treated drinking water is wasted owing to an estimated 240,000 annual water main breaks (ASCE 2017). As reported by the American Water Works Association (AWWA) in 2016, $1 trillion is needed for the maintenance of water infrastructure to meet the future demand for water (ASCE 2017). Similarly, the Canadian Infrastructure Report Card revealed that 23% of the water infrastructure is in poor to fair condition (CIRC 2016). As reported by Folkman (2018), the failure rate of water mains is increasing exponentially over time with the majority of failures occurring in gray CI pipes, whereas the lowest failure rate occurs in PVC pipes.

In Canada, the investment in pipe maintenance between 1985 and 2006 has increased from $57 billion to $125 billion, respectively (Mirza 2007). Rehabilitation and replacement (R&R) of water mains are ongoing activities owing to aging caused by operational and environmental factors, such as climate change and temperature (Rogers and Grigg 2009).

Purpose of the Study

The physical mechanisms that lead to the failure of water mains are complex and not fully understood. Therefore, the main objectives of the present study are to (1) develop prediction models for determining the average time to failure; and (2) assess the sensitivity of the prediction model to different factors using global sensitivity analysis (GSA).

Literature Review

There are several factors that can negatively impact the condition of buried pipes. In structural and geotechnical studies, Kamel and Meguid (2012) found that loss of contact between pipelines and the surrounding soil can increase the contact pressure and, consequently, stresses in the pipe material. Kaddoura and Zayed (2018) examined the effect of erosion voids around sewer pipelines, as such voids may reduce the service life of a pipeline. They identified five factors that contribute the most to the occurrence of voids around sewer pipelines: soil type, bedding type, pipeline depth, pipeline age, and water table.

Kishawy and Gabbar (2010) concluded that the integrity of pipelines has to meet the increasing pressure of demand on the pipelines. They summarized the factors that could threaten the integrity of subsurface pipelines as (1) incorrect operation, (2) pipe material, (3) corrosion and cracking mechanics, (4) earth forces such as earthquakes and landslides, and (5) weather-related factors such as rough seas, high winds, and temperature. Thus, the design of pipelines should not only rely on pressure and stress criteria but also on other indispensable factors responsible for pipeline integrity.

Evaluating the factors that affect the condition of water mains is essential for owners to meet the following criteria: (1) developing strategies that mitigate the likelihood of pipe failure; (2) the costs that results from pipe failure, such as flooding and traffic disruption; and (3) avoiding the early replacement of a pipe, that is, before the end of its economic life. Deterioration of water mains can result from static and dynamic factors that may cause long- and/or mid-term failure of water distribution systems. Fig. 1 illustrates static, dynamic, and operational factors that affect the failure of water mains in both short- and long-terms. Static factors, such as pipe material, diameter, and age, are fixed over time; whereas dynamic factors, including environmental and operational factors such as soil moisture, temperature, landslide, external stresses, and water pressure, potentially change over time (Farmani et al. 2017; Kleiner and Rajani 2001; Wang et al. 2009). In addition, there are physical mechanisms that can lead to pipe breakage and failure, such as

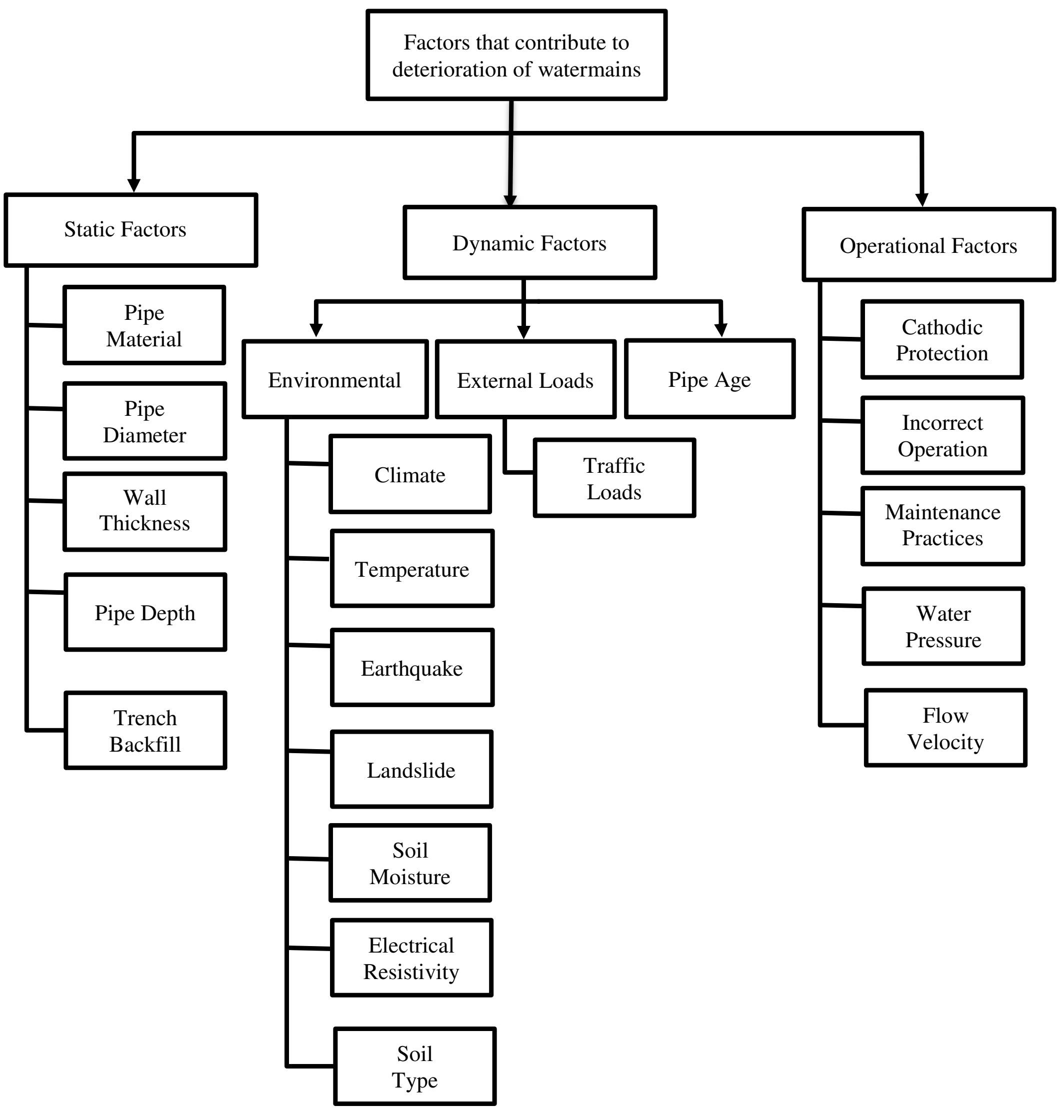

Fig. 1. Factors affecting the condition of water mains in both short- and long- terms.

Table 1. Summary of failure prediction models of water mains

Reference	Variables	Methodology	Output
Yamijala et al. (2009)	Diameter, material, length, land use, soil type, soil moisture, temperature	MLRM, MERM, GLM	Likelihood of break
Christodoulou (2011)	Age, material, incident type, diameter, number of breaks	PRM	Failure rate
Francis et al. (2014)	Material, diameter, age, demographic variables, and temperature	BBNs	Pipe breaks
Shirzad et al. (2014)	Hydraulic pressure, diameter, length, age, and depth	ANN, SVR	Failure rate
Kabir et al. (2015)	# of bursts, age, diameter, length, soil resistivity, soil corrosivity	BMA, RM	Failure rate
Demissie et al. (2017)	Length, diameter, number of previous failures, type of service connection, freezing index, thawing index, rainfall deficit, and soil corrosion	DBN	Pipe breaks
Farmani et al. (2017)	Length, diameter, age, temperature, freezing index	EPR	Pipe breaks
Parvizsedghy et al. (2017)	Age, pipe size, soil type, groundwater depth, installation quality, C-factor, and surface type	RM	Failure rate
Kaushik et al. (2017)	Length, diameter, age, # of bursts, depth, material, pressure, and flow	LRM	Pipe breaks
Sattar et al. (2019)	Length, diameter, soil type, and # of pipe failures	EML	Failure time
Snider and McBean (2018)	Length, diameter, soil type, material, and # of pipe failures	GBDTM	Failure time
Winkler et al. (2018)	Length, material, age, diameter, variables, and # of pipe failures	BDT	Failure or not

Note: MLRM = multilinear regression model; MERM= multivariate exponential regression model; GLM = generalized linear model; PRM = possession regression model; BDT = boosted decision tree; RM = regression model; ANN = artificial neural network; BMA = Bayesian model average; EPR = evolutionary polynomial regression; LRM = logistic regression model; EML = extreme machine learning; GBDTM = gradient-boosting decision tree model; SVR = support vector regression; BBNs = Bayesian belief networks; and DBN = dynamic Bayesian network.

(1) internal loads resulting from operational pressure and external loads due to traffic, soil overburden, and frost loads; and (2) structural properties of the pipe, pipe-soil interaction, and quality of installation (Rajani and Kleiner 2001). Manufacturing flaws, excessive forces, and human errors have been found to have significant impact on the performance and service life of CI water mains (Makar et al. 2001).

Failure Prediction Models of Water Mains

Physical, Statistical, and Machine Learning Models

Previous studies extensively implemented physical and statistical models to examine the condition of utility pipes such as water mains. In physical models, pipe failure was determined by measuring the response under a variety of environmental or other loading conditions that would negatively affect the integrity of the pipe structure. Physical models do not require a huge amount of historical data to develop. However, they require material properties, which are generally not readily available (Wilson et al. 2017).

Statistical models, on the other hand, embody a set of assumptions based on observed data that are generally obtained from many cases that describe the pipe behavior. They can be implemented in a case study using various levels of input data for distribution water mains (Kleiner and Rajani 2001). As reported by Mavin (1996), the main fragility of statistical models is that "while failures generally increase with pipe age, there is a wide variation of individual assets" in which "links appear with soil type and weather fluctuations."

In recent years, machine learning has become more favorable in the prediction of pipe failure. Algorithms can be developed to help decision makers to identify pipes that require urgent attention or those in need of immediate replacement (Liu and Kleiner 2014; Zhou and Chen 2018). Machine learning could be applied to predict the failure of water mains with the growth of population and aging of pipelines (Kettler and Goulter 1985; Zhou and Chen 2018). Data mining is defined as the process of extracting new and useful information from big databases. Machine learning is the technical basis of data mining that is used for finding, studying, and describing constitutional patterns in data (Witten et al. 2016). It is also a subset of artificial intelligence (AI) that emerged from computer science focusing on the study of algorithms (Bishop 2006). Several articles have been published on the use of statistical and machine learning models to predict the failure of pipelines such as water mains. Table 1 presents a summary of some of the most recent failure prediction models of water mains and variables that were considered in the model. Yamijala et al. (2009) developed statistical models that are multilinear regression, multivariate exponential regression, and logistic generalized linear model (GLM) to estimate the likelihood of pipe breaks on the basis of several factors: pipe diameter, pipe material, pipe length, land use, temperature, soil moisture, and soil type. Results showed that GLM performed better than other models. In another work, Christodoulou et al. (2011) developed possession and Cox statistical regression models based on various factors, such as pipe age, pipe material, incident type, pipe diameter, and number of breaks, in order to predict the failure rate. Francis et al. (2014) built a model that contained several factors (pipe material, pipe diameter, pipe age, demographic variables, and temperature) to predict pipe break by using Bayesian belief networks (BBNs) of water mains on the basis of historical data for a large city in the mid-Atlantic US. Shirzad et al. (2014) suggested that support vector machine (SVM) over artificial neural network (ANN) could be used to predict the failure rate of water mains. Both models were developed on the basis of several factors: (1) hydraulic pressure, (2) pipe diameter, (3) pipe length, (4) pipe age, and (5) depth. Kabir et al. (2015) conducted a study to predict the failure rate of water mains using Bayesian and regression models based on number of breaks, pipe age, pipe diameter, pipe length, soil resistivity, and soil corrosivity. Results proved that the Bayesian model performed better than the regression models when limited data were available. Demissie et al. (2017) developed dynamic Bayesian network (DBN) to predict pipe break on the basis of pipe length, pipe diameter, number of previous failures, type of service connection, freezing index, thawing index, rainfall deficit, and soil corrosion. Farmani et al. (2017) studied static and dynamic factors that impact the condition of water mains. The dataset was divided into homogeneous groups according to the similarity in water main features and following *k*-means clustering approach. The evolutionary polynomial regression (EPR) model was then developed to predict the number of failures based on soil type, pipe diameter, and pipe age. Kaushik et al. (2017) developed a model using logistic regression model to predict pipe breaks using static features such as pipe diameter, pipe length, and pipe material. The study was applied to a real-world dataset obtained from a water utility in Europe. Sattar et al. (2019) suggested the use of the extreme learning machine (ELM) to predict the failure of water mains based on historical data from the Greater Toronto area. The model was trained by using 9500 instances of failure records based on pipe length, pipe material, pipe protection method, and pipe diameter. Using a decision tree to predict the time of the next water main failure, Snider and McBean (2018) developed a gradient-boosting algorithm. The researchers trained the model on a dataset derived from water utility for ductile iron pipes in North America. The results suggested the use of a gradient-boosting algorithm when dealing with a large dataset of pipe failure to predict the time of the next water main failure. Winkler et al. (2018) presented the ensemble decision tree (EDT)-based model using historical data from Austria to predict water main failure. The boosting technique was used to improve the model performance, and 50% of the available data were utilized to train the model based on various factors that are physically, geographically, and historically derived. Some researchers have claimed that there is a significant relationship between pipe diameter and number of breaks (Christodoulou 2011; Kettler and Goulter 1985; Yamijala et al. 2009).

The Motivation to the Study and Research Gaps

The failure of water mains is considered a serious problem in North America and has been studied for the last 40 years through the application of a variety of methods. Through the use of physical and statistical models, extensive research has been conducted to study the conditions and failure of water mains, respectively. However, in recent years, machine learning has become more favorable in the prediction of water main failure and can be implemented to assess the future state of water mains whenever proactive maintenance is needed. A prediction model is one of the fundamental components that helps decision makers to determine the best maintenance plans and to prioritize the rehabilitation actions. Computational intelligence, on the other hand, promotes high-level awareness of system conditions using historical records and sensory data. Using statistical models, previous studies have focused on the failure prediction of water mains with small or large diameters. But, as regards the techniques of AI, such as ensemble modeling, in the prediction of water main failure, research efforts remain limited, hence the need for this study. Therefore, three models are developed to (1) predict the failure of various types of materials and different sizes of water mains; and (2) choose the best model in terms of performance. These models are: EDT, ANN, and l_2. In general, ensemble models perform better than a single model (Drucker 1997). In previous studies, ensemble models were applied in classification-based models to classify whether there is failure or not, according to Table 1, refer to Winkler et al. (2018). However, in this study the EDT is of a regression-based model that aims to predict the average time of water main failure, which is a continuous variable. Whereas, l_2 is developed as it performs better than a linear regression model in case of multicollinearity between predictors (Khalaf and Shukur 2005). In other words, l_2 is a form of linear regression with a penalty term that is imposed to address multicollinearity as well as to improve model performance. The ANN, on the other hand, can capture nonlinear correlation between predictors and the model output. This study is an attempt to use machine learning to predict water main failure.

Modeling Techniques

The study mainly utilizes three main intelligent approach schemes. These schemes are as follows: ANN, l_2, and EDT.

ANN

ANNs are tools that have been widely utilized in solving many complex real-world problems. Feedforward network is extensively applied to recognize patterns and learn from their interactions with the environment. The architecture of multilayer perceptron (MLP) of feedforward neural network includes a set of artificial neurons within the input and output layers. Intermediate layers of neurons, on the other hand, are placed between the input and output layers. They are called hidden layers as they contain hidden neurons and do not interact with the external environment (Basheer and Hajmeer 2000; Jafar et al. 2010). These neurons calculate a weighted sum of the input signals (I) and then pass it (the sum) into an activation function, according to Eq. (1)

$$\boldsymbol{y} = f\left(\sum_{i=1}^{I} \boldsymbol{w_i x_i} + \alpha_0\right) \tag{1}$$

where x_i for $i = 1, 2, \ldots; I$ = input signal; w_i = estimated parameter; f = activation function; and α_0 = bias/intercept (Haykin 1994).

l_2 Models

The main purpose of the simple linear regression analysis is to predict the relationship between one or more continuous target variables, given a set of input (x_i). A linear combination of these variables is built by fitting a linear relationship between target/dependent variable (y) and predictor/independent variables (x_i), as per Eq. (2) (Tibshirani 1996). The linear combination is called linear regression model, which is a linear function of the estimated parameters (w_i) and input variables (x_i). Although, some predictors are linearly correlated while others are nonlinearly correlated with the model output; linear regression remains an efficient model that has been widely applied to predict the failure of water mains. The least-square method can be applied to calculate the estimated weights, as expressed in Eq. (3). The l_2 is a linear regression, where constraints (λ) are set to control the size of the weights in order to reduce the variance between actual and predicted values, Eq. (4). Solution are indexed by tuning the parameter (λ), where λ is chosen for whichever coefficients are not rapidly changing and have meaningful signs (Tibshirani 1996; Zou and Hastie 2005)

$$\boldsymbol{y}(\boldsymbol{x}, \boldsymbol{w}) = \alpha_0 + \sum_{i=1:n} \boldsymbol{w}_i x_i \tag{2}$$

$$\boldsymbol{w} = (\boldsymbol{x^T x})^{-1} \boldsymbol{x^T y} \tag{3}$$

$$\boldsymbol{w_\lambda^{ridge}} = (\boldsymbol{x^T x} + \boldsymbol{\lambda I_P})^{-1} \boldsymbol{x^T y} \tag{4}$$

EDT-Based Model

Decision tree models are employed to predict the deterioration of pipelines because of the simplicity of the method in creating trees that help with decision making (Winkler et al. 2018). The ensemble model is applied to improve the accuracy of the prediction model and reduce the prediction error by using multiple predictors. The two well-known techniques of ensemble learning are called bagging and boosting. Both can be used to build a committee of regressors that may be superior to a single regressor. Each regressor in bagging and boosting is trained on different subsets of the training dataset, and these are randomly selected. In bagging, each regressor is trained independently on samples that are randomly picked with replacement from the original samples of the training dataset. Different models are constructed by applying the same base learning algorithm and then averaging the prediction of all the regressors (Bühlmann and Hothorn 2007; Shrestha and Solomatine 2006). Whereas in boosting, the first regressor is trained on samples that are randomly picked from the original training dataset. Then all the training patterns pass through the first regressor to adjust the prediction error (Drucker 1997; Elith et al. 2008).

Each function prediction is associated with a weight (α_m) that is updated during the iterative training algorithm. Eq. (5) shows the combination of all weak predictors to obtain a strong predictor. In boosting, that is by the AdaBoost-based technique, the weights $(w_1, w_2, \ldots, w_N)$ of the individual observations $(x_i, y_i), i = 1, \ldots, N$ are initialized to $w_i = 1/N$

$$G(x) = sign\left(\sum_{m=1}^{M} \alpha_m G_m(x)\right) \tag{5}$$

These weights are reweighted after each iteration, so the probability patterns that are most in error are more likely to be fixed in the training datasets. The patterns that are most in error are those in which the difference between their predicted and actual values is significant (Bühlmann and Hothorn 2007; Winkler et al. 2018).

GSA

GSA was carried out to test the robustness of the model. This was achieved by searching for errors in the model and observing unexpected relationships between the inputs and outputs. In GSA, all inputs are varied simultaneously in comparison with local sensitivity analysis. GSA can be defined as the study of the uncertainty in the output of a mathematical model to identify the key variables whose uncertainty affects most the output over their entire range of interest (Homma and Saltelli 1996; Ramakrishnan and Bailey-Kellogg 2008; Tarantola et al. 2006).

A variance-based method is the most common one to compute sensitivity indices for GSA (Homma and Saltelli 1996; Pianosi et al. 2015; Song et al. 2013; Tarantola et al. 2006).

Suppose the model

$$\boldsymbol{Y} = f(\boldsymbol{X}_1, \ldots, \boldsymbol{X}_\mathrm{i}) \tag{6}$$

where Y = output, and the inputs $X_1, \ldots, X_p$ = independent random variables defined by probability distributions that define the uncertain knowledge in the system. The purpose of this method is to study the contribution of each input variable to the output variance. In other words, the importance of an input variable (X_i) on the

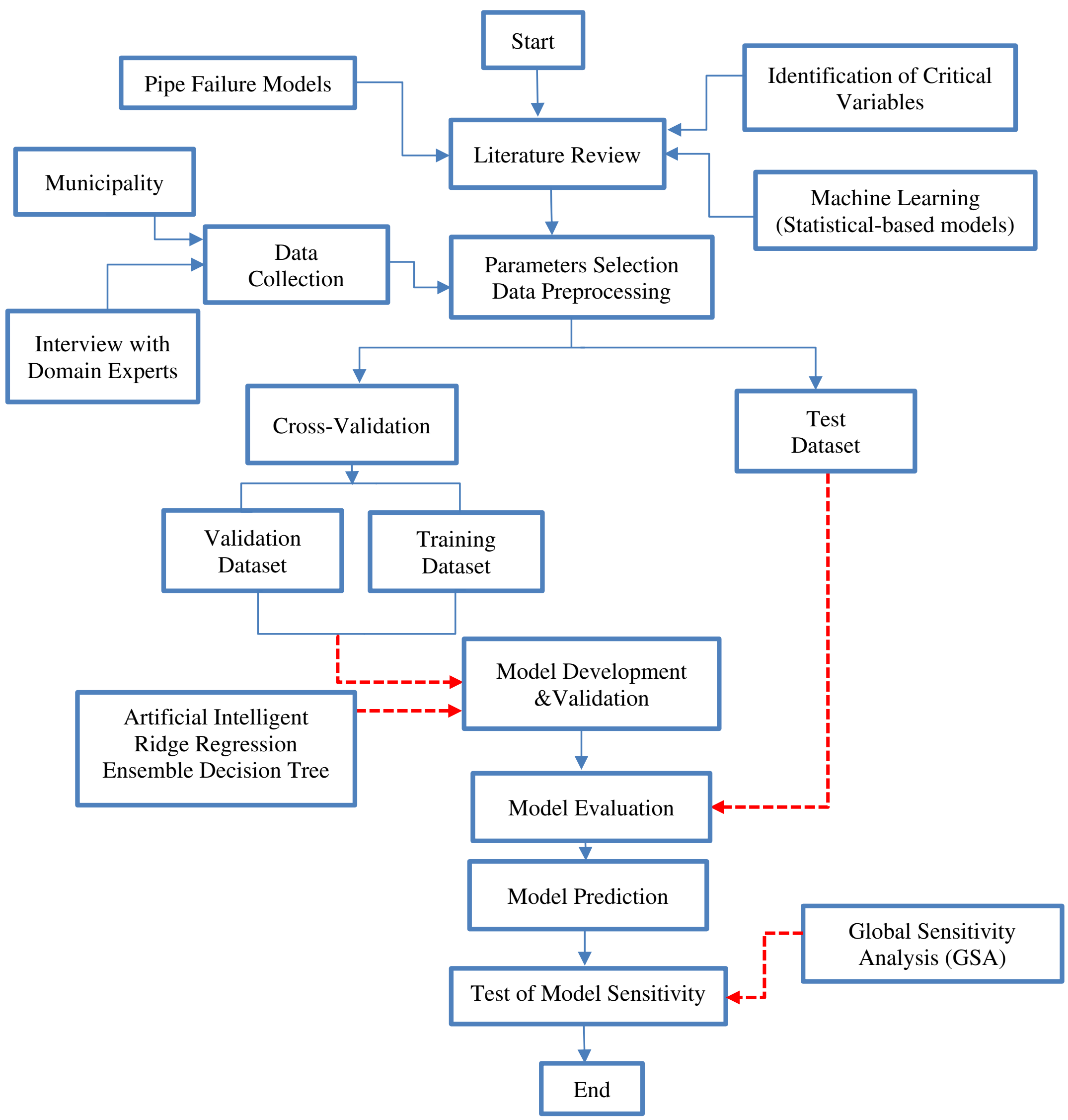

Fig. 2. Proposed framework for failure prediction of water mains.

Table 2. Summary of the failure database records from the municipality of Sainte-Foy, Quebec City

Variable	Pipe material				
	CI	DIL	DIN	PVC	Hy
Total number of pipes	526	205	217	125	45
Total pipe length (m)	3,734.04	15,673.96	14,657.9	9,196.245	3,371.854
Average pipe length (m)	71.0	71.50	72.23	73.57	74.93
Diameter (mm)	100–600	38–600	100–450	50–750	150–400

variance of Y (Homma and Saltelli 1996; Pianosi et al. 2015; Sobol 1993, 2001). The first-order indices can be calculated using the conditional variance, where $S_i < 1$, as shown in Eq. (7) (Sobol 1993; Zhan et al. 2013)

$$S_i = \frac{V_i}{V(Y)} = \frac{V(E(Y|X)}{V(Y)} \tag{7}$$

Research Methodology and Model Development

Fig. 2 illustrates the framework of the proposed model that can predict average time to failure in water mains in order to assess the condition of subsurface infrastructure and help decision makers either in main rehabilitation or/and replacement services. The study has developed three models including ANN, l_2, and EDT in order to select the one with satisfactory performance for failure prediction of water mains. The developed models are evaluated employing root mean square error (RMSE), mean absolute error (MAE), and coefficient correlation (R). In addition, the developed models are tested on data collected from Quebec City water mains.

Data Collection Method

The historical failure database used in this study is obtained from the municipality of Sainte-Foy, Quebec. The database consists of recorded information, such as pipe material, diameter, and length; year of installation; and breaks. It spans a 15-year period (1987–2001) for each individual pipe within 432 km of a water distribution system. The database contains five types of pipe materials, namely, gray CI, ductile iron with lining (DIL), ductile iron without lining (DIN), PVC, and hyprescon/concrete (Hy) pipes. The majority of breaks occurred in CI, DIN, DIL, PVC, and Hy at a rate of 47.05%, 19.41%, 18.34%, 11.18%, and 4.02%, respectively, as summarized in Table 2. In a statistically-based model, dummy variables can be used to represent qualitative data that take the value of either 0 or 1 (Garavaglia and Sharma 1998). Thus, each material was defined as a dummy input and fed into the model as a vector of two possible values, 0 or 1.

Data Preprocessing and Cross-Validation

A descriptive analysis was utilized to check the missing values of the dataset. The database was divided up so that 90% of the total database was dedicated to training and validation (cross-validation), and 10% to testing the final model. Cross-validation (k-fold) was applied to validate and examine the performance of each selected model. It was also applied to evaluate the parameter selection and learning process of all the developed models. The database (N) was randomly split into five subsets (the folds), $N_1, N_2, N_3, \ldots, N_5$, of approximately equal sizes. The model was tested and validated k times, hence $t \in \{1, 2, \ldots, k\}$. The model was trained on (N/N_t) and validated on (N_t). The testing dataset, on the other hand, was then used to test the performance of the final developed models. Some outliers were removed to improve the performance of the model.

Model Development

Models were developed and coded to predict the time to water main failure on the basis of pipe material, diameter, and length by using MATLAB version R2018a software. The time to water main failure is defined as the time from installation date to the 1st break.

ANN Model

ANN-MLP model was developed by using ANN Toolbox in MATLAB R2018a software. As previously explained, MLP is a class of feedforward neural network, and used to refer to ANN that consists of multiple layers of perceptrons. It was applied using backpropagation algorithm with adaptive learning rate when searching for the best parameters for building a final model for predicting the failure of water mains. The parameter-tuning approach was conducted for the ANN-MLP model to reach the optimal solution. Fig. 3 depicts the representation of ANN-MLP model used to search for the optimal solution. ANN-MLP consisted of one input and one output layer with six neurons, and one neuron, respectively. The performance of ANN-MLP was also examined at different numbers of hidden neurons in the range of [2, 20].

l_2 Model

The l_2 has one parameter called lambda (λ), as explained previously in Eq. (4). The model was coded to calculate the weights of each quantitative and qualitative variables in the model. The quantitative variables are the pipe length (L) and diameter (D), whereas the qualitative variables are the pipe materials that were defined as dummy variables in the model, namely, PVC, DIL, DIN, CI, and Hy. The l_2 model, on the other hand, was tested on different values of (λ) in the range of [0, 2] to find the optimal solution when validating the performance of the model. Eq. (8) depicts the developed equations of l_2

$$y = \alpha_o + \beta_1 L + \beta_2 D + \beta_3 \mathrm{PVC} + \beta_3 \mathrm{DIN} + \beta_4 \mathrm{DIL} + \beta_5 \mathrm{CI} \tag{8}$$

where y = predicted time to pipe failure; α_o = intercept/bias; and β_k = estimated weights/coefficients.

EDT Model

Fig. 4 depicts the typical structure of bagging [Fig. 4(a)] and boosting [Fig. 4(b)] ensemble learning models, which were explained previously in EDT-based model. Drucker (1997) reported that if boosting is not equivalent to bagging, then in most cases, it is better than bagging. Therefore, the boosting technique was applied in the present study to improve the prediction accuracy. EDT model using

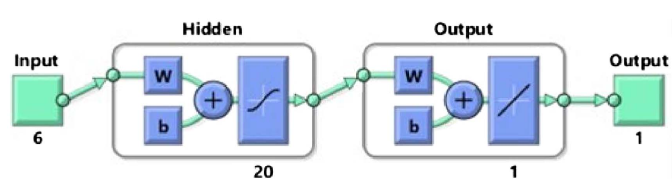

Fig. 3. Initial representation of ANN-MLP. b = bias; and w = weights.

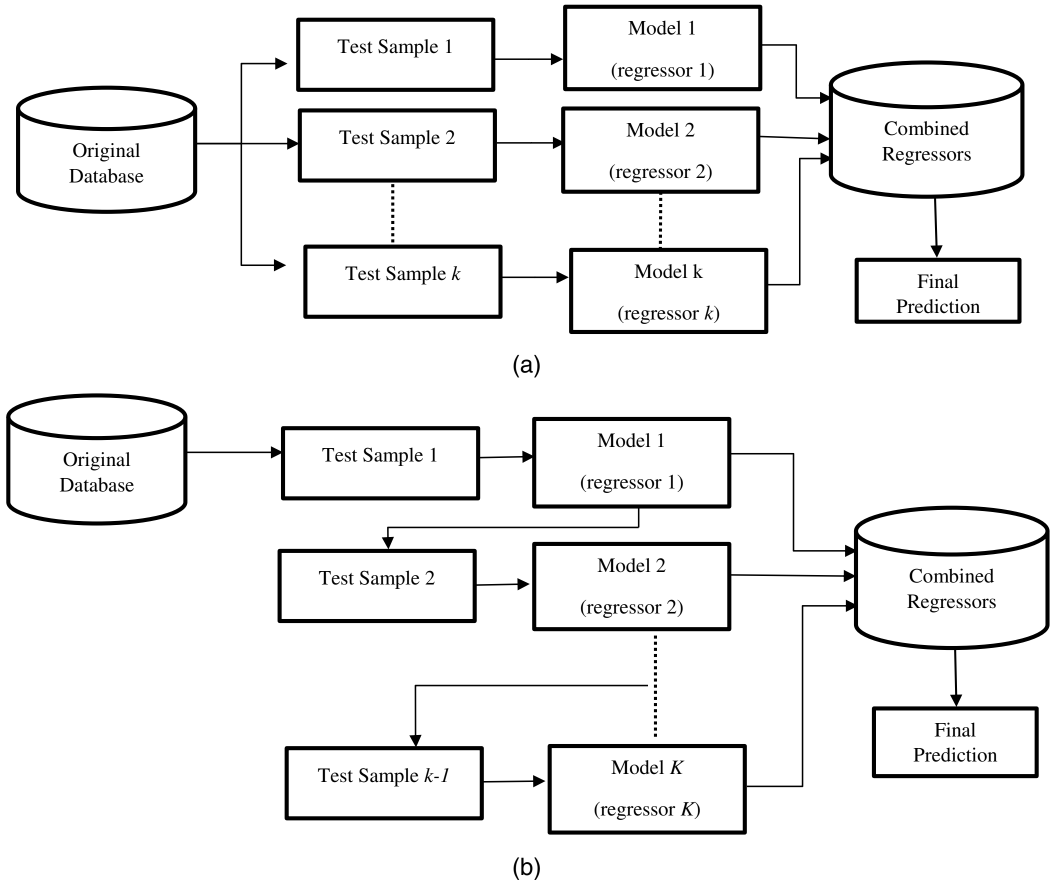

Fig. 4. Typical architecture of ensemble learning models: (a) bagging-based model; and (b) boosting-based model.

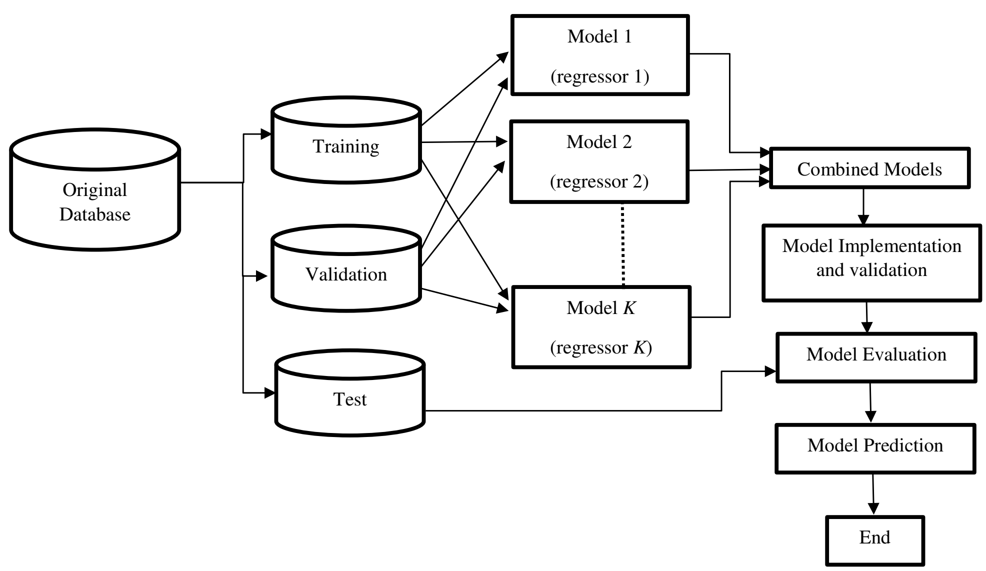

Fig. 5. Comprehensive methodology of EDT model using boosting technique.

the boosting technique is a combination of two algorithms: (1) a regression tree that creates a relationship between predictors and response on the basis of recursive binary splits, and (2) boosting, which is an ensemble technique used to combine simple models to improve the accuracy of the model. Fig. 5 depicts a comprehensive methodology of EDT model using the boosting technique. Regression trees were constructed and trained on randomly selected samples from the training dataset. The models were then combined to predict the failure of water mains. A modification was applied to the Adaboost.R algorithm as suggested by (Drucker 1997; Freund and Schapire 1996). First, a single decision tree model was developed by tuning different hyperparameters such as maximum split and parent size to eliminate the risk of overfitting. However, the model performance was similar to the default setting.

Afterward, the EDT model was developed and coded as follows (Fig. 6):

- Assign a weight for each sample in the training dataset $Z_i = \frac{1}{N_k}$, where N_k is the sample number of training dataset; thus, the initial probability of each sample being in the training set is $p_i = Z_i / \sum Z_i$.
- Pick N_k with replacement to form a training dataset for each regressor (regression tree).
- Construct regression tree machines such that each machine makes a hypothesis (h_r:$\boldsymbol{x} \rightarrow \boldsymbol{y}$, where R is the number of iterations/regressors).
- Train each regression tree machine R by using every N_k.
- Calculate the loss using a nonlinear function ($Loss_i = \frac{|y_i - \hat{y}|^2}{\max(|y_i - \hat{y}|)^2}$) and the average loss ($\overline{Loss} = \sum_{i=1}^{N_k} \mathrm{L}_i p_i$).
- Update the weight by $Z_i = Z_i \times \beta$, where $\beta = \frac{\overline{Loss}}{1 - \overline{Loss}}$.
- Calculate the weighted median (W) for each regression tree; $\mathrm{W} = \sum_{I:h_r \leq y} \log(\frac{1}{\beta_r})$.
- Calculate the cumulative predictions $CP(x) = sign(\sum_{r=1}^{R} W_r CP_r(x))$.

GSA of the Developed Models

GSA was later carried out to test which variable was more critical to the model output. Random samples of different sizes (N) were generated to obtain the desired probability density function for x_i that covers the input space of interest. For the simplification of testing the model, a uniform distribution was assumed for each variable in which each outcome has the same probability that it will be the outcome. The model was then evaluated at different levels of N designs to test the reliability of the model. Finally, a sensitivity index (S_i) was computed for each x_i at different N point designs by using Eq. (10). The first-order main effect was calculated as it does not require a significant computational cost, and higher orders are often neglected in sensitivity analysis (SA).

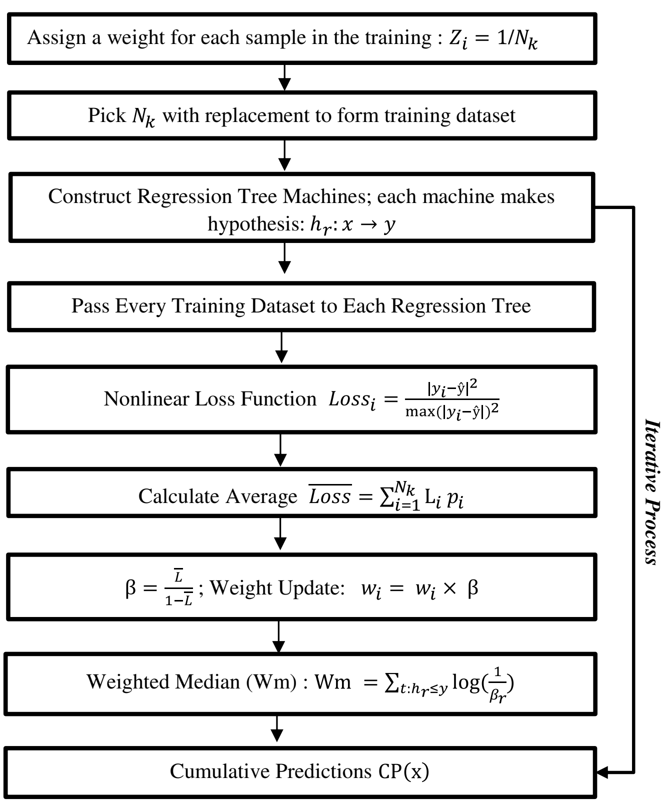

Fig. 6. Model development of EDT model.

Performance Assessment of the Developed Models

A set of mathematical validation equations was used to evaluate the performance of the model. A comparison between the actual (y_i) and the predicted values ($\hat{y}$) was accomplished as a main evaluation procedure for assessing the performance of the model using three techniques, namely, RMSE, MAE, and R, Eqs. (9), (10), and (11), respectively (Botchkarev 2018; El-Abbasy et al. 2014; Sarsam 2019). R is a statistical measure that calculates the association between two variables. It is also well-known as Pearson's correlation coefficient. In this study, the strength of the relationship between two variables (A and B) was calculated using R expressed in Eq. (11) (Sarsam 2019)

$$\mathrm{RMSE} = \sum_{i=1}^{n} \sqrt{(\hat{y} - y_i)^2} \tag{9}$$

$$\mathrm{MAE} = \frac{1}{n} \sum_{i=1}^{n} |\hat{y} - y_i| \tag{10}$$

$$\mathrm{R} = \frac{cov(A, B)}{\sigma_A \sigma_B} \tag{11}$$

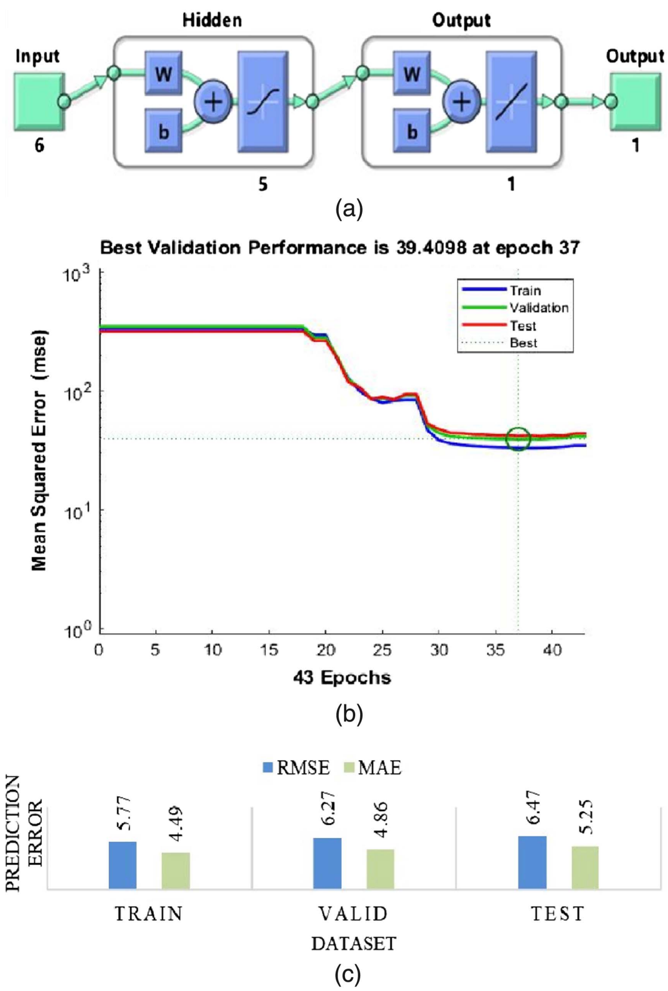

Fig. 7. ANN-MLP and its performance: (a) ANN-MLP model; (b) ANN-MLP training performance; and (c) ANN-MLP model prediction performance. b = bias; and w = weights.

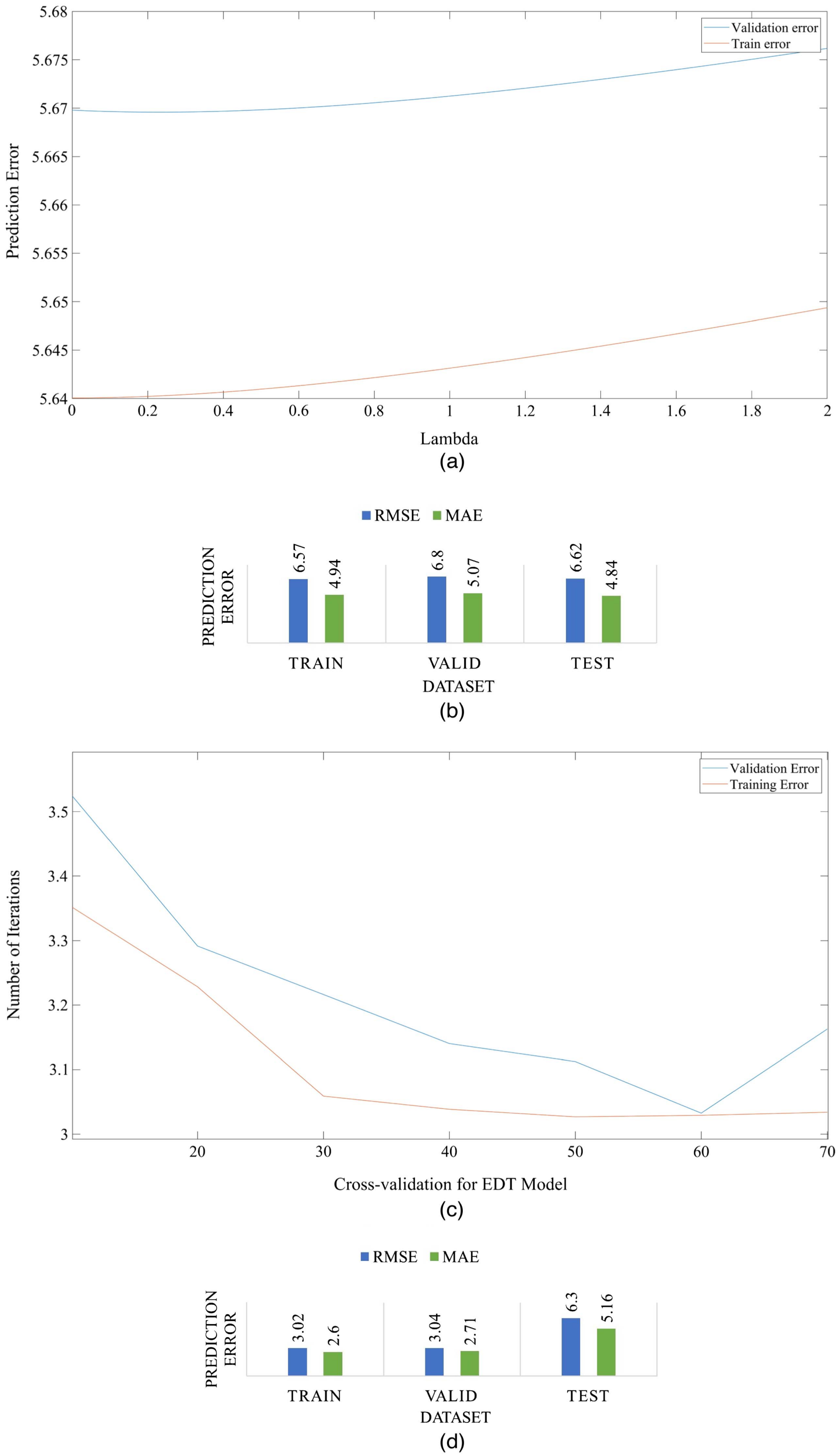

Fig. 8. l_2 model outputs: (a) cross-validation; and (b) prediction performance; and EDT model outputs: (c) cross-validation; and (d) prediction performance.

Table 3. Ridge coefficients and model equation of l_2 model

Variable	Ridge coefficient	Mean	Std	Ste	Max
Intercept	17.6394	—	—	—	—
L	1.1428	0.391	0.214	0.0068	1
D	−3.8146	0.231	0.081	0.0026	1
PVC	−12.7269	—	—	—	—
DIL	−5.0187	—	—	—	—
DIN	4.9950	—	—	—	—
CI	16.8929	—	—	—	—

Note: Categorical variables: L = length; D = diameter; Std = standard deviation; and Ste = standard error.

Model Implementation and Validation

Model Setup for Artificial Neural Network (ANN-MLP)

The aim of the cross-validation is to examine the performance of ANN-MLP, using backpropagation algorithm with adaptive learning rate when searching for the best parameters to build failure prediction model of water mains for decision makers. ANN-MLP trained until the validation error reached the optimal at epochs 52. The output and input layers consisted of one neuron with a linear activation function and six neurons, respectively. The weights are randomly initialized in the range of [0, 1]. After tuning the parameters, the best ANN-MLP was constructed with one hidden layer and five hidden neurons with tangent hyperbolic sigmoid as shown in Fig. 7(a). The learning rate was also set at 0.38. These parameters were chosen based on the performance evaluation of ANN-MLP in cross-validation. Fig. 7(b) shows the performance of ANN-MLP when the lowest mean square error (MSE) reached the minimum value (optimal solution) at epoch 37. The final model was tested on a test dataset and the result shows satisfactory performance in terms of the prediction error of water main failure prediction model, using ANN-MLP [Fig. 7(c)].

Model Setup for Ridge Regression (l_2)

Cross-validation showed that the validation error reached optimal solution at $\lambda = 0.2$ [Fig. 8(a)]. Therefore, after tuning the parameter and performance evaluation of l_2, λ was set at 0.2. The performance of the final model of water main failure prediction using l_2 is shown in Fig. 8(b). Table 3 illustrates ridge coefficients of qualitative and quantitative variables, and descriptive statistics of quantitative variables of the l_2 model. Eq. (12) shows the equation of the developed model, using l_2

$$y = 17.6394 + 1.1428\mathrm{L} - 3.8146\mathrm{D} - 12.7269\ \mathrm{PVC} - 5.0187\ \mathrm{DIN} + 4.9950\ \mathrm{DIL} + 16.8929\ \mathrm{CI} \tag{12}$$

Table 5. Evaluation of different models using a set of mathematical validation equations

Models	RMSE	MAE	R
l_2	5.42	4.21	0.90
ANN	6.47	5.25	0.84
EDT	6.34	5.01	0.88

Model Setup for EDT

The study utilized the parameter-tuning approach for EDT model to reach the optimal solution. The model was trained on different numbers of iterations/regressors R and the initial weight was assigned for each sample in the training ($Z_i = 1/N_K$). EDT model, on the other hand, was trained and validated on different scenarios. Scenario 1: some outliers were removed. Scenario 2: all outliers were removed. Scenario 3: assumed minimum time to water main failure = 5 years. Scenario 4: assumed minimum time to water main failure = 10 years. Scenarios 3 and 4 showed the highest performance. However, Scenario 1 was selected to train the model as, logically speaking, pipe failure could happen at an early age because of manufacturing flaws, human errors, or any other odd/unknown reasons. Fig. 8(c) depicts the performance of the evaluation of the model at different numbers of iterations/regressors TR. The optimal solution was achieved when TR = 60. Thus, after parameter tuning and model validation, TR was set at 60. Fig. 8(d) illustrates the final performance of the EDT model for the failure prediction of water mains. Additionally, different decision tree-based models were developed and the results show that EDT proposed in this study performed better than other investigated methods (Table 4).

Findings and Discussion

Comparison of the Three Intelligent Models

The study employed a set of mathematical validation equations to test the performance of each model. The evaluation matrices showed that l_2 has RMSE = 5.42, MAE = 4.21, and R = 0.90. However, ANN has RMSE = 6.47, MAE = 5.25, and R = 0.84. EDT, on the other hand, has RMSE = 6.34, MAE = 5.01, and R = 0.88 (Table 5). Results revealed that all models were able to predict the failure of water mains. Fig. 9 illustrates the predicted values versus actual values of time to pipe failure and shows high R was achieved by all the models developed. Results also prove that there is no high variation between predicted values and actual values, and there are no outliers (Fig. 10).

Prediction Error of Different Pipe Categories

The RMSE of different pipe categories was calculated on the basis of the pipe material. Results indicated that the prediction error of

Table 4. Performance of different decision tree-based models based on validation error

Models	Method	Cross-validation	No. of iterations	RMSE	MAE
Single decision tree	Fitrtree[a]	fivefold	None	7.58	5.98
Ensemble model	Fitrensemble[a] Boosting technique	fivefold	50	7.31	5.69
EDT model	Fitrtree[a] Boosting technique	fivefold	60	3.10	2.7138

[a]Applied function in MATLAB 2018a.

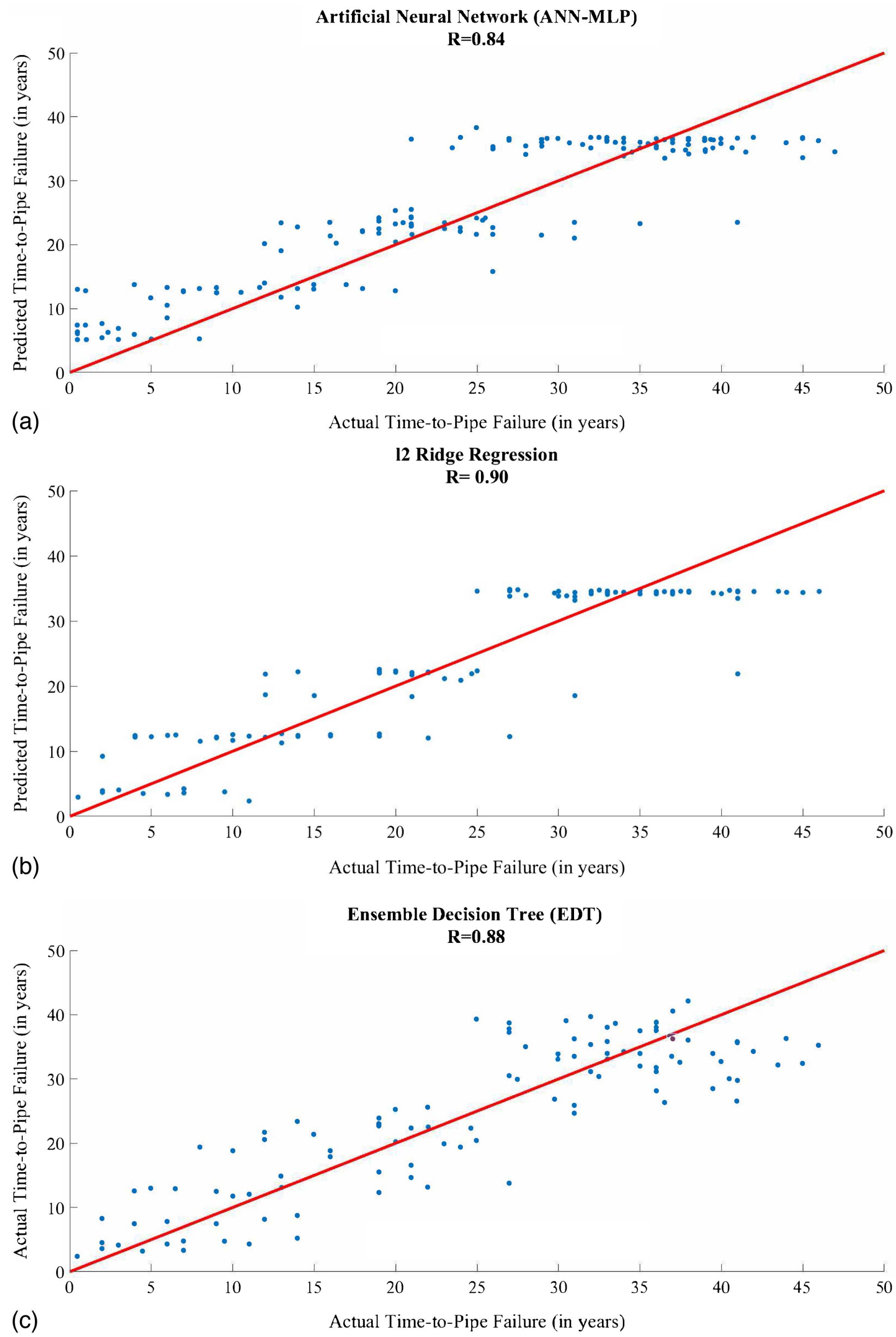

Fig. 9. Actual versus predicted values of water main failure prediction: (a) ANN-MLP; (b) l_2; and (c) EDT.

water main pipes made of PVC was lower than that of other materials and the total average error. However, the prediction error resulting from CI material was higher than the total average error [Fig. 10(a)]. Thus, the results suggest that the model may perform better when predicting the failure of each material individually. For materials such as PVC, Hy, DIN, and DIL, the prediction error is lower than the total average error.

GSA for EDT

EDT model was again selected for analyzing and testing the reliability of the model because of its simplicity and computational efficiency in terms of creating trees that assist decision making. This is also the case because of the flexibility of decision tree-based models in coping with both discrete and continuous variables. Overall, however, all models can help decision makers to avoid the unexpected failure of water mains in the future.

The results of the GSA showed that CI, Hy, and DIL are the most critical variables to the output of the model (average age to failure of individual pipe) followed by DIN and PVC [Fig. 10(b)]. Fig. 10 shows the sensitivity indices and standard error for each material at $N = 50{,}000$, $N = 100{,}000$, and $N = 1{,}000{,}000$. The standard error for each material decreases as the size of generated samples increases.

Different pipe geometry and material types are considered in this study. The relationship between the pipe materials with different pipe lengths (regardless of diameter) and the average time to pipe failure is depicted in Fig. 11(a). Whereas, the correlation of

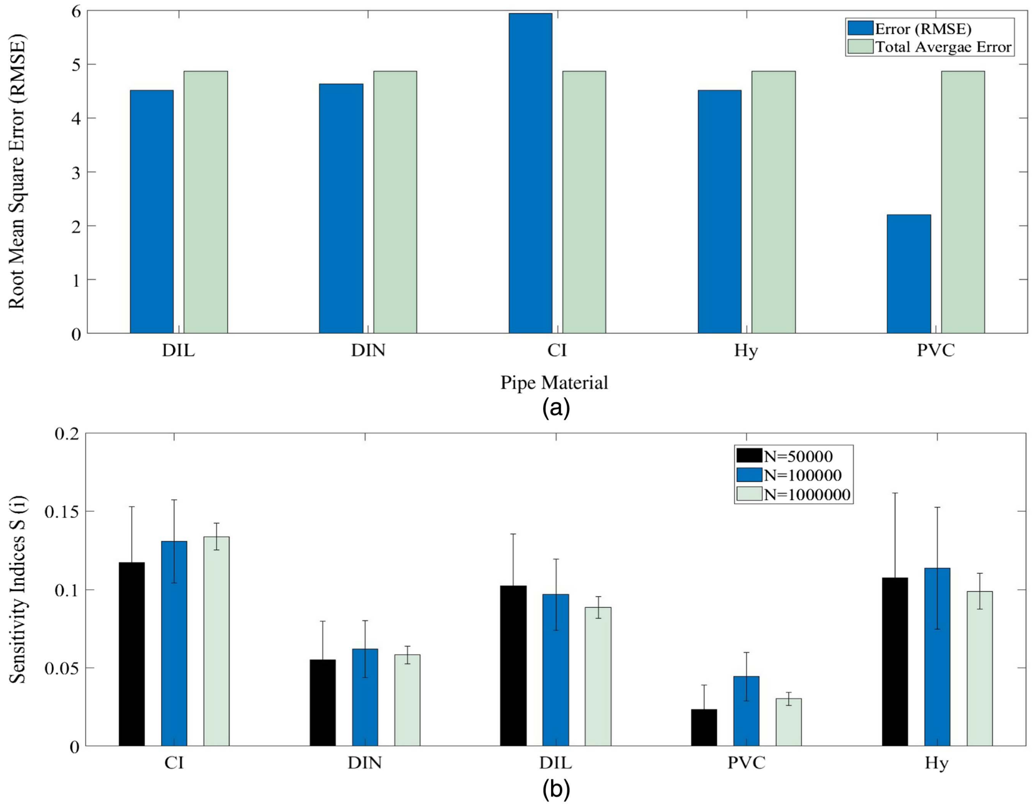

Fig. 10. (a) Error (RMSE) of pipe materials; and (b) sensitivity indices of pipe materials.

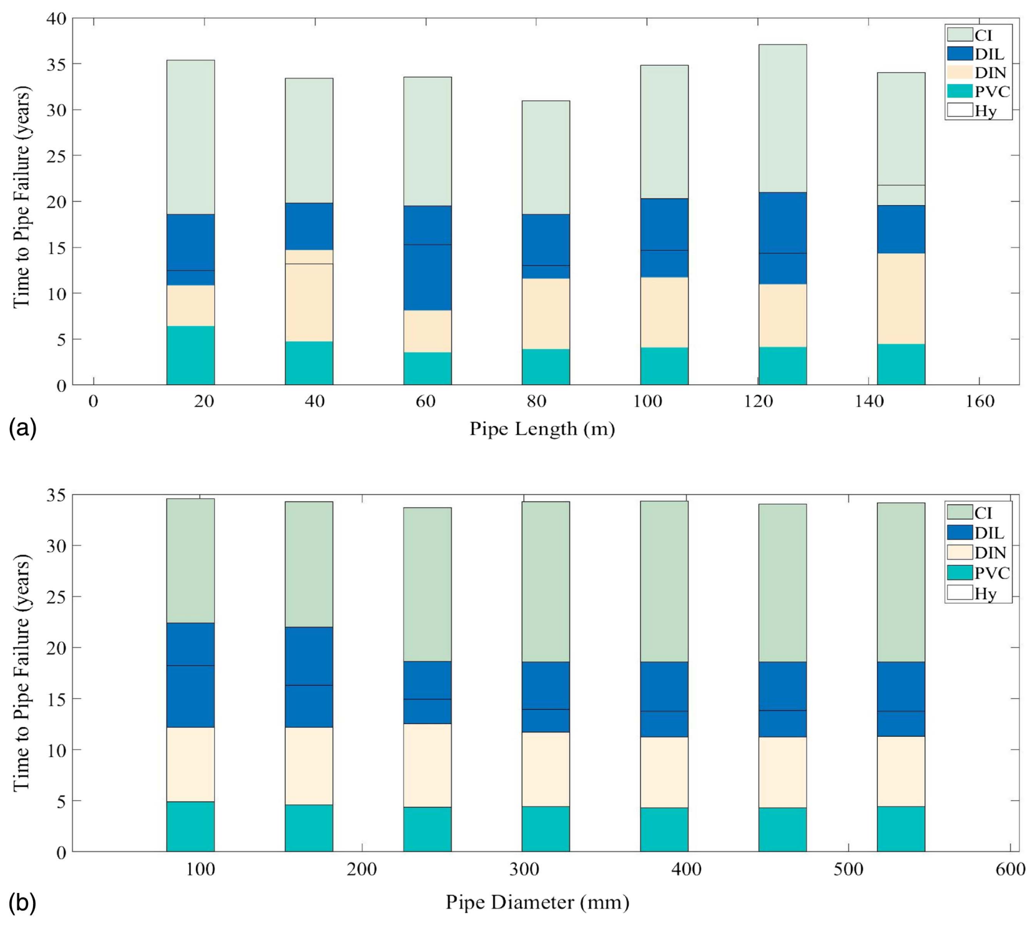

Fig. 11. Average time to pipe failure verses: (a) pipe length (meters); and (b) pipe diameter (millimeters).

pipe materials with different pipe materials (regardless of length) versus the average time to pipe failure is shown in Fig. 11(b). Results showed that a relatively strong correlation exists between the pipe length and the time to pipe failure (in years) for CI, DIN, and Hy. However, the time to pipe failure (in years) is relatively constant with the length of PVC and DIL [Fig. 11(a)]. On the other hand, time to pipe failure (in years) has slightly changed with the diameter of DIL, DIN, and Hy at a certain point and then remained constant [Fig. 11(b)]. This is attributed to the fact that the majority of pipe failure occurred in pipes with small diameters, that is, between 100 and 250 mm. Furthermore, the output is almost constant with the diameter for other materials. It can be concluded, therefore, that the failure of water mains mostly relies on pipe material and length. Similarly, previous studies showed that pipe length affects the condition of the pipe (Demissie et al. 2017; Fares 2008; Ismaeel 2016; Karimian 2015; Mohammed 2016; Sattar et al. 2019; Wang 2006). Additionally, as pointed out by Zangenehmadar (2016), the potential of water main failure increases with the increase of the pipe length. The results proved that the failure of water mains is correlated with the pipe length. El Chanati (2014), on the other hand, reported that the pipe length contributes to the failure of water mains.

Conclusion

The purpose of this study was to develop intelligent models that could assist decision makers to avoid unexpected water main failure. The developed models were trained on data collected from the municipality of Sainte-Foy, Quebec City. The data consisted of three physical variables that were expected to contribute to the failure of water mains with respect to pipe material, length, and diameter. The results revealed that the boosting technique reduced the prediction error of single decision tree.

Overall, all models showed good performance and were satisfactorily able to predict the failure of water mains. However, EDT is recommended owing to the simplicity and computational efficiency of decision tree-based models in terms of creating trees for decision making and coping with both discrete and continuous variables. GSA showed that CI, Hy, and DIL are the most critical variables to the output of the model. Besides, the results revealed that a relatively strong correlation exists between time to pipe failure (in years) and the length of CI, DIN, and Hy. The results also indicated that the output slightly changes with the diameter for Hy, DIN, and DIL, whereas the model output is almost constant with the diameter for other materials. Nevertheless, some pipe materials, such as CI, DIL, and Hy, last longer than others. It can, therefore, be concluded that the failure of water mains mostly relies on pipe material and length. The provided data, on the other hand, are limited and there are other variables that are crucial for identifying the cause of water main failure. Considering especially the fact that the failure of water mains is a dynamic process and time-dependent in nature, dynamic/environmental variables will be considered in the future. Finally, it is worth mentioning that the performance of prediction models relies on the quality of the data collected and on the selection of appropriate algorithmic techniques. However, the database is limited and adding more variables that affect the failure of water mains may improve the accuracy of the model.

Data Availability Statement

Some data, models, and codes used during the study are available from the corresponding author by request. Data provided by the municipality of Sainte-Foy, Quebec cannot be shared as it is confidential.

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