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Predicting the Timing of Water Main Failure Using Artificial Neural Networks

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Abstract: Effective management of aging water distribution infrastructure is essential for preserving the economic vitality of North American municipalities. Historical failures within Scarborough, Ontario, Canada, reveal a seasonal pattern to water main failures, with the majority of failures occurring during the very cold winter months. Extensive installation of cement mortar lining and cathodic protection have extended the life span of aging water mains and reduced escalating failure rates. Artificial neural networks are found to be capable of predicting the time to failure for individual pipes using a range of pipe-specific attributes, including diameter, length, soil type, construction year, and the number of previous failures. The developed models have correlation coefficients ranging from 0.70–0.82 on instances reserved for evaluating predictive performance and have utility on an asset-by-asset basis when planning water main inspection, maintenance, and rehabilitation. Simulated failure scenarios indicate a return to high failure rates if cement mortar lining and cathodic protection are not extended to all candidate pipes in the distribution system. **DOI: 10.1061/(ASCE)WR.1943-5452.0000354.** © *2014 American Society of Civil Engineers.*

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Introduction

Water distribution pipes placed in North America following World War II are rapidly approaching the end of their effective design life. As these critical pieces of buried infrastructure age, they deteriorate and lose resilience to imposed stresses, which leads to their failure. The consequences of water main failure include reduced revenue from water lost during transmission, interrupted access to safe drinking water, compromised water quality after the ingress of contaminants into the pipeline, and possible damage to surrounding infrastructure (i.e., overlying roadways, buried electrical utilities, and nearby building foundations). Frequent occurrences of water main failure place tremendous financial strain on cities such as Toronto, Ontario, where there are 1,300 water main failures each year (Schuster and McBean 2008). Toronto Water's recommended capital plan for 2012–2020 acknowledges their responsibility to carry out water main rehabilitation work in a timely manner to ensure clean and accessible drinking water is provided for generations to come. With a planned investment of $1.13 billion in water main rehabilitation over the next 10 years, they aim to reduce the number of annual water main failures, restore revenue from lost water sales, and eliminate Toronto's backlog of rehabilitation work by 2020 (Toronto Water 2011).

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Utility managers need access to location-specific information on pipe failure if rehabilitation programs are to be successfully implemented. Given this, substantial efforts have been made to model pipe failure in a manner amenable to the planning of rehabilitation activities. Shamir and Howard (1978) used regression analysis to predict failure rates (number of failures per unit length per year) for homogeneous groups of pipes installed under similar conditions. Walski and Pelliccia (1982) further explored this approach and incorporated data on pipe age, diameter, and the number of previous breaks. Clark et al. (1982) used regression to predict the time to first failure and the number of failures after the first event, although predictive capabilities of the models were not demonstrated. Kettler and Goulter (1985) found failure rate to be inversely proportional to pipe diameter in 43 km of cast-iron pipes studied in Winnipeg, Manitoba. Goulter and Kazemi (1988) used regression to determine the probability of subsequent pipe breaks given that at least one failure had occurred. Malandain et al. (1999) used regression to predict failure rates for pipes in Lyon, France, grouped according to structural and environmental factors. Boxall et al. (2007) used regression to examine the influence of diameter, age, length, and soil conditions on annual burst rates of cast-iron and asbestos cement water pipes in the United Kingdom. Regression models developed in Wang et al. (2009) for pipes in a large water distribution system provided insight into the influence of material, age, and length on annual break rate but could not be used to predict the timing of future failures.

A number of studies have developed time-related failure risk relationships using a branch of statistics known as survival analysis. Andreou et al. (1987a) found early stages of pipe failure could be characterized by a semiparametric proportional hazards model and a Poisson-type model could be used to predict failure later in an asset's life. A coefficient of determination of 0.46 was achieved when predicting failure in older pipes (Andreou et al. 1987b). A similar approach was described in Eisenbeis (1994) and Brémond (1997), where proportional hazards models were used to investigate the influence of failure history on the expected number of failures in large water distribution networks in France. Gustafson and Clancy (1999) used a semi-Markov process to model failure of

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thick wall, medium wall and thin wall water mains in Saskatoon, Saskatchewan. While the model was found to be adequate for predicting interbreak times for water mains in a historical dataset, it could not effectively predict the timing of future failure. Mailhot et al. (2000) focused on the development of statistical failure models for municipalities with short recorded histories of pipe breaks. Rostum (2000) developed proportional hazards and nonhomogeneous Poisson process models to determine the influence of pipe length, diameter, age, soil conditions, and the number of previous failures on cast-iron and ductile-iron water main failure times in Norway. Pelletier et al. (2003) used survival analysis to predict the total annual number of failures for three Quebec municipalities. While the coefficient of determination for the model was low (0.39—attributed to the variation of natural processes involved as pipes grow older), the model was useful for exploring the impact of different pipe replacement scenarios on the annual number of pipe failures. Park et al. (2008) analyzed 92 pipes (each having at least five failures) to develop failure rate models with coefficient of determination values of 0.48–0.59. Kleiner and Rajani (2010) used a nonhomogeneous Poisson process to predict the expected number of breaks for groups of cast-iron pipe using 40 years of historical break data from western Canada. While predictions of the total number of breaks over a 5 year period were accurate, predictions for individual pipes were not as valid. Survival analysis presented in Christodoulou (2011) provided insight into the change in hazard rate over time for pipes grouped by pipe diameter and type of failure (i.e., corrosion or tree root penetration).

Data mining represents an alternative approach to water main failure modeling that draws on the fields of artificial intelligence, machine learning, and statistics so that valuable information can be extracted in a manner that circumvents assumptions of time-related failure behavior required by statistical approaches. Sacluti et al. (1999) used artificial neural networks (ANNs) to predict the number of failures in a distribution system based on a 7-day weather forecast. While the model was incapable of predicting failure for individual pipes in the network, its utility lay in the short-term planning of cold-weather maintenance. Babovic and Drecourt (2000) modeled break potential using self-organizing feature maps and Bayesian networks trained with 3,175 repair jobs carried out from 1928 to 1995 on water pipes in Copenhagen, Denmark. Ahn et al. (2005) used neural networks to examine the influence of water and soil temperature on water pipe failure using a failure record collected over one year. Neural network analysis was used in Christodoulou et al. (2007) to examine the influence of various attributes on pipe life-cycle behavior in Limassol, Cyprus. The number of previous failures was found to have the greatest influence on failure, followed by pipe material, diameter, and traffic loading. Al-Barqawi and Zayed (2008) predicted water main condition ratings (0–10) for individual water mains in three Canadian municipalities using an ANN with physical, environmental and operational inputs. Fares and Zayed (2010) developed a hierarchical fuzzy expert system to determine water main condition ratings (0–10) using a knowledge base of failure established through a literature survey of municipal experts and a database of 544 water main failures collected in Moncton, New Brunswick. Ho et al. (2010), Tabesh et al. (2009), and Jafar et al. (2010) used neural networks to predict the total number of water main failures in a distribution system. Asnaashari et al. (2013) examined changing water main failure rates in Etobicoke, Ontario, and found neural networks to be better suited to the prediction of failure rate than multiple regression methods.

At this point, data mining approaches have focused on either the prediction of failure rate, condition score, or the total number of failures. These predictions are useful when planning rehabilitation activities (i.e., water mains with the highest rate of failure should be a priority for replacement), but do not provide information on when failures are likely to occur. In response, a novel approach to the prediction of the time to failure for individual water mains using artificial neural networks is described herein. Background information on the case study area of Scarborough, Ontario, is first presented—with a focus on the positive impact of cathodic protection and cement mortar lining on the annual number of water main failures. Unique instances extracted from historical records are used to train neural networks capable of predicting the time to failure in years, for individual water mains, using attributes such as diameter, length, year of construction, and the number of previous failures. Models developed for asbestos cement, cast-iron, and ductile-iron water mains have correlation coefficients of 0.70–0.82 and have utility on the planning of inspection, maintenance, and rehabilitation activities on an asset-by-asset basis.

Case Study Scenario

The 5.5 million residents of the Greater Toronto Area (GTA) rely on an extensive network of piping infrastructure for their drinking water. The average pipe in the 5,850-km distribution network is 55 years old—with 17% of the water mains older than their effective design life of 80 years and 6.5% more than 100 years old (City of Toronto 2012). The historical database of water main failures for the district of Scarborough used in this research consists of year of construction, pipe material, length, diameter, soil type, year of cement mortar lining (if done), year of cathodic protection (if done), and pipe failure dates recorded from 1962 to 2005 (up to the tenth break of an individual pipe). The dataset contains 6,346 water mains installed from 1905 to 2000 with a system length of 1,021 km. These water mains are constructed from asbestos cement, cast iron, ductile iron, or PVC with lengths ranging from 0.28 to 1,634.31 m and diameters ranging from 32 to 1,500 mm. A total of 3,500 water mains have never failed, while 2,846 have failed at least once. A brief summary of the failure dataset is presented in Table 1.

A First Look at Pipe Failure in Scarborough

Fig. 1 depicts the significant reduction in annual pipe failures following the implementation of cathodic protection (CP) in 1986 and cement mortar lining (CML) in 1988. The CML process removes rust build-up on the inside of the water main and then lines the internal pipe surface with a thin layer of cement. The CP technique involves the attachment of zinc or magnesium sacrificial anodes to the water main. While typically used for metallic pipe, CP can also be used to protect metallic fittings and connections on nonmetallic pipes such as asbestos cement and PVC. The trend line in Fig. 1 illustrates the decrease in the number of yearly failures that began in the mid-1980s, which is directly correlated to Scarborough's vigorous implementation of pipe protection. The 117 failures in 2005 are directly comparable to the 84–127 annual failures that occurred over the 1962–1965 period, even though the length of the distribution system had doubled from 558 km in 1962 to 1,021 km in 2005. CP has been shown to be effective for extending the lifespan of aging pipes and reducing pipe failures in a number of other studies. Kleiner et al. (2003) illustrated a decrease in the total annual number of failures following the implementation of CP for 1,750 km of cast-iron and ductile-iron pipes in Ottawa, Ontario. A 17% reduction in break frequency was observed after the implementation of CP in Winnipeg, Manitoba (Rajani and Kleiner 2003). Case studies in Des Moines, Iowa, indicate CP extends the lifespan of existing

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Table 1. Summary of the Scarborough Water Main Failure Dataset

Attribute	Material of construction			
	Asbestos cement	Cast iron	Ductile iron	PVC
Total number of pipes	463	3,793	1,747	343
Construction year	1950–1991	1921–2000	1955–1996	1978–1991
Pipe length (m)	1–831	0.3–978	0.3–1,634	0.6–731
Average pipe length (m)	194	153	171	149
Total pipe length (km)	90	582	299	50
Diameter (mm)	150–400	50–1,500	100–600	150–300
Number in sand/gravel	173	589	209	85
Number in silt/clay	290	3,204	1,538	258
Number of pipes with CP	9	514	785	10
Number of pipes with CML	0	1,801	137	0
Number with zero failures	337	1,530	1,300	333
Number with at least one failure	126	2,263	447	10
Number of failures in total	248	8,204	1,454	12

water mains by 20 years at less than 10% of the replacement cost of the piping (Schramuk and Klopper 2005). A study of water main failure in the GTA (Schuster and McBean 2008) indicates significant cost savings can be achieved through CP—where repair costs for 150-mm diameter ductile iron pipes with CP over 10-years represented one-third of non-CP repair costs (CAD$100,000 versus CAD$300,000).

Fig. 2 illustrates the reduction in the number of days per year with a recorded failure that occurred after the implementation of CML and CP. Most water mains in the early 1960s were relatively new and there were only 100 days per year with a single failure and 50 days with multiple failures. As pipes began to deteriorate in the 1980s, the number of days in a year with at least one break rose to more than 200. At that point in time there were approximately 100 days each year with multiple failures occurring at different locations in the distribution system and mobilization of repair equipment and construction crews must have been challenging and expensive. Days with multiple failures increase the likelihood that members of the general public will be without safe water as they wait for repairs in another part of the City to be completed before construction crews reach their neighborhood. CML and CP implementation brought the annual failure days back to the more manageable levels of 50 years ago.

Scarborough water mains fail at variable rates within the year. Fig. 3 displays a box-whisker plot of monthly failures during 1962–2005 and shows how failures have historically been highest during the colder winter months (November–25, December–36, January–43, and February–32). Approximately 60% of all pipe failures occur during the colder winter months and this seasonal variation in water main failure frequency has been previously documented in Lackington and Large (1980), Newport (1981), Kettler and Goulter (1985), Chambers (1994), Habibian (1994), and Saegrov et al. (1999). Blair et al. (2011) note that pipe bursts in Scotland are highest during November to March when minimum air temperatures remain below zero for long periods of time.

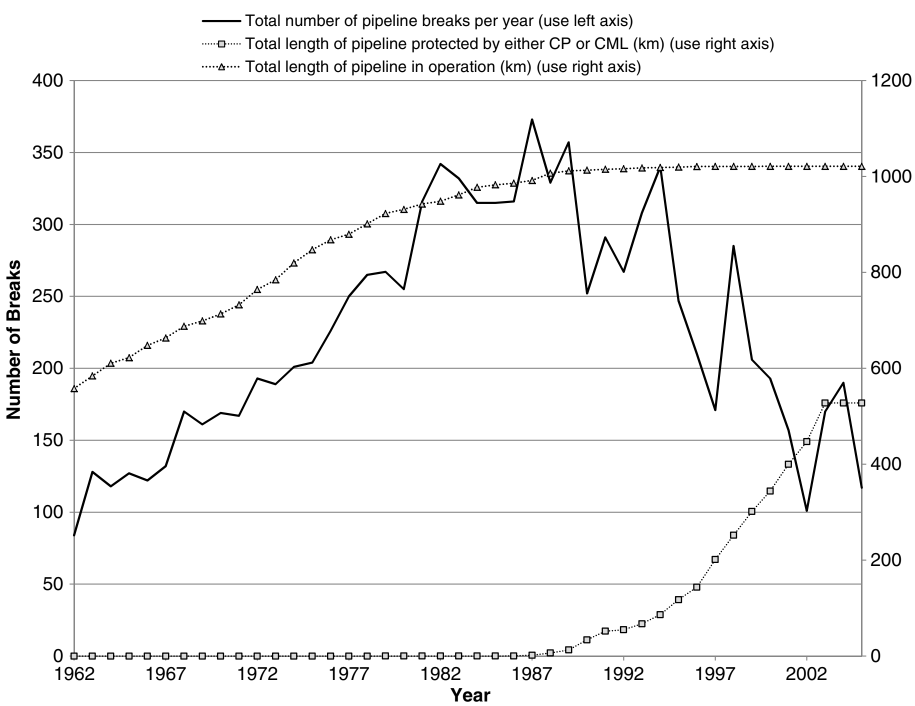

Fig. 1. Impact of CML and CP on the total number of watermain failures each year in Scarborough

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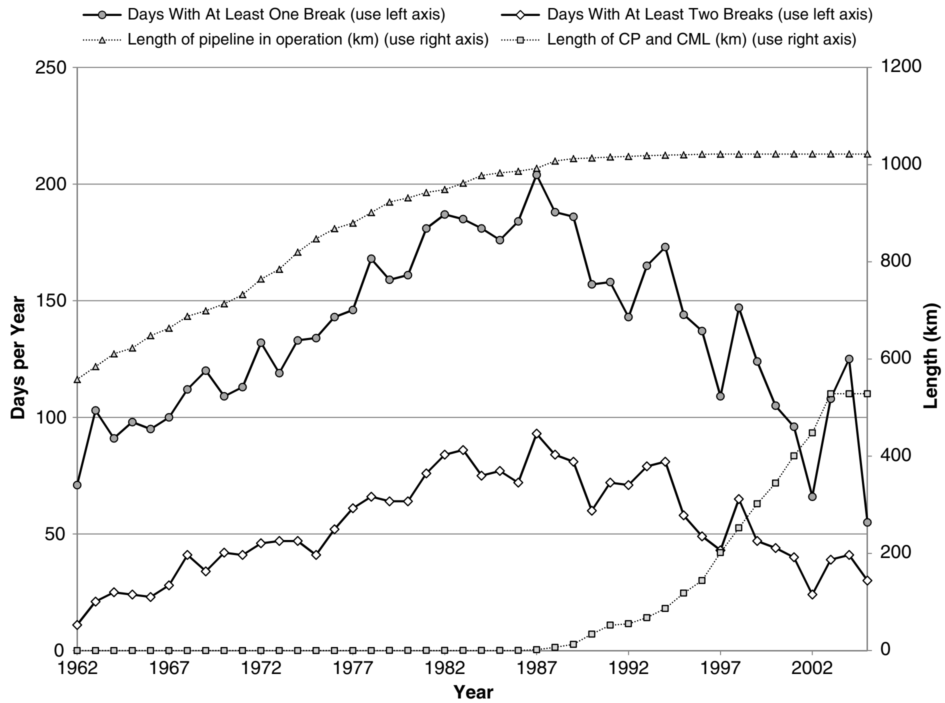

Fig. 2. Impact of CML and CP on the total number of days each year with a water main failure

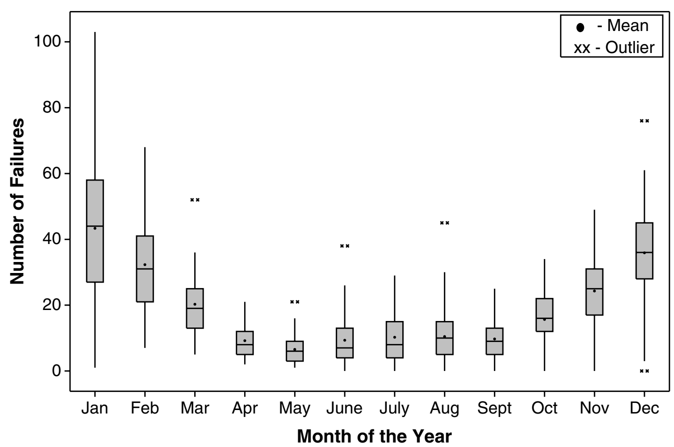

Fig. 3. Seasonal variations in the total number of water main failures

Artificial Neural Network Model Development

Artificial neural networks (ANNs) mimic the information processing capabilities of the human brain and have revolutionized the way complex, real-world problems can be modeled in engineering, science, and finance. ANNs are capable of approximating any nonlinear relationship between inputs and outputs in a way that is robust against noise in the training data (Mitchell 1997). Although a variety of architectures have been developed over the years, the archetypical network is the feedforward multilayer perceptron (MLP)—consisting of an input layer, an output layer, and one hidden layer of neurons (Hinton 1992). While each neuron on its own is only capable of performing simple computations, the hierarchical organization of interconnected neurons with variable weights allows the network to learn to make predictions based on historical instances (El-Din and Smith 2002).

In general terms, neural networks are trained to perform a task by learning from a set of training instances or examples. Each instance presented to a network takes the form $\langle \rightarrow x, t \rangle$ where $\rightarrow x$ is a vector of attribute values and t is a target/observed value. The instances of water main failure used to train the neural networks were extracted from Scarborough's historical dataset of failure. The average time to first failure for pipes constructed post-1962 was found to be 16 years, so instances of pipe failure were extracted using pipes installed from 1946 to 2005. Although some individual pipes constructed from 1946 to 1961 may have experienced a failure prior to the first logged failures in 1962 (as variations in break rate may occur due to such factors as variations in construction practice), expansion of the modeling dataset in this manner reduces the likelihood of missing failures in older pipes.

Unique instances of failure were extracted using the recorded dates for each individual failure. To illustrate the process of developing the modeling dataset, consider a cast-iron pipe installed in 1955 with a diameter of 300 mm, length of 80 m, buried in sand/gravel, cement mortar lining installed in 1991, cathodic protection installed in 1990, and two failures recorded in 1985 and 2002. The first instance of failure would have the following attributes: construction year = 1955, diameter = 300, length = 80, soil = 0 (sand/gravel), CML = 0 (failure occurred prior to CML installation in 1991), CP = 0 (failure occurred before CP installed in 1990), number of previous failures = 0 and time to failure = (date of break 1 – installation date) = (1985–1955) = 30 years. The attributes for the second instance of failure would be similar, with the exception of: CML = 1 (date of the second break came after CML installation), CP = 1 (date of second break came after CP installation), number of previous failures = 1 and time to failure = (date of break 2 – date of break 1) = (2002–1985) = 17 years. Inclusion of the number of previous failures is a necessity as it separates instances of failure extracted from a pipe's failure history that would otherwise have identical attributes but different observed time to failure.

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Table 2. Attributes and Targets Used for Neural Network Development

Material	Attribute	Type	Range
Asbestos cement (248 instances of failure)	Diameter	Numeric	150–400 mm
	Length	Numeric	18.79–828.55 m
	Construction year	Numeric	1952–1984
	Soil type	Nominal	0–sand/gravel (109 instances) 1–silt/clay (139 instances)
	Previous failures	Numeric	0–9 failures
	Time to failure	Numeric	0–48 years
Cast iron (7,795 instances of failure)	Diameter	Numeric	50–600 mm
	Length	Numeric	1.82–970.29 m
	Construction year	Numeric	1946–1985
	Soil type	Nominal	0–sand/gravel (598 instances) 1–silt/clay (7,197 instances)
	CML protection	Nominal	0–no CML (7,414 instances) 1–CML (381 instances)
	Cathodic protection	Nominal	0–no CP (7,744 instances) 1–CP (51 instances)
	Previous failures	Numeric	0–9 failures
	Time to failure	Numeric	0–56 years
Ductile iron (1,453 instances of failure)	Diameter	Numeric	100–400 mm
	Length	Numeric	1.98–1260.10 m
	Construction year	Numeric	1957–1985
	Soil type	Nominal	0–sand/gravel (99 instances) 1–silt/clay (1,354 instances)
	CML protection	Nominal	0–no CML (1,446 instances) 1–CML (7 instances)
	Cathodic protection	Nominal	0–no CP (1,377 instances) 1–CP (76 instances)
	Previous failures	Numeric	0–9 failures
	Time to failure	Numeric	0–32 years

Extraction of individual failure instances from each of the 2,699 pipes that have failed at least once created 9,508 unique instances of pipe failure.

Neural networks for predicting the time to failure in years for asbestos cement, cast-iron, and ductile-iron water mains were trained using the online back-propagation with momentum algorithm available in *IBM SPSS Statistics 20*. The algorithm searched through the n-dimensional Euclidean space of n network weights for the best hypothesis (i.e., the weights that give the best prediction of the observed value). PVC water mains failed 12 times over the 1982–2005 period, and this small sample size prevented the development of a model for PVC water main failure. The pipe-specific inputs for each ANN model are described in Table 2.

The attributes and observed time to failure for each instance presented to the neural network were standardized by subtracting the mean and dividing by the standard deviation to prevent differences in magnitude among the variables from influencing network weights. The instance datasets available for each water main material were randomly partitioned into training, testing, and holdout test sets using a 70-15-15 split ratio. Division into these data sets ensured convergence on a globally optimal solution through use of the early-stopping cross validation technique (Mitchell 1997). The training set was used to train the model, the testing set was used to track errors during training and prevent overtraining, and the holdout set was used to evaluate the predictive capabilities of the ANN. A double-loop technique was used to search for the optimal network architecture, where the outer loop ran through a range of 1–20 hidden neurons configurations and the inner loop ran through a series of 20 random weight initializations to ensure evaluation of the full range of network performance. The best-performing/optimal network architecture had the lowest sum-of-squares error (SSE) between the predicted and observed time to failure. All networks were trained using a hyperbolic tangent transfer function for each hidden neuron and the identity function for the output layer.

Results

Table 3 presents the network architectures and performance for the asbestos cement, cast-iron, and ductile-iron water main models. The relative error is the ratio of the sum-of-squares error for the dependent variable (time to failure) to the sum-of-squares error for the null model (the model where the mean value of the time to failure is used as the predicted value for each instance). The relative errors were constant across the three datasets, indicating successful prevention of overtraining.

The optimal asbestos cement ANN consisted of five input nodes (length, diameter, soil, year of construction, and number of previous failures) and four hidden neurons. While the training set of data available for developing the asbestos cement model was the smallest of the three materials, the correlation coefficient for the 37 instances reserved for evaluating the trained ANN was 0.70, indicating the model is capable of providing a realistic estimate of the time to failure for the 463 asbestos cement water mains in the distribution system.

Table 3. Predictive Performance of ANNs on Training, Validation, and Testing Datasets

Material	Architecture	Dataset	Instances	SSE	Relative error	R-value
Asbestos cement	5 – 4 – 1	Training	174	39.60	0.46	0.74
		Testing	37	6.293	0.42	0.76
		Holdout	37	—	0.56	0.70
Cast iron	7 – 6 – 1	Training	5,457	1,387.34	0.51	0.70
		Testing	1,169	309.75	0.53	0.69
		Holdout	1,169	—	0.50	0.70
Ductile iron	7 – 4 – 1	Training	1,017	172.40	0.34	0.83
		Testing	218	37.86	0.32	0.82
		Holdout	218	—	0.34	0.81

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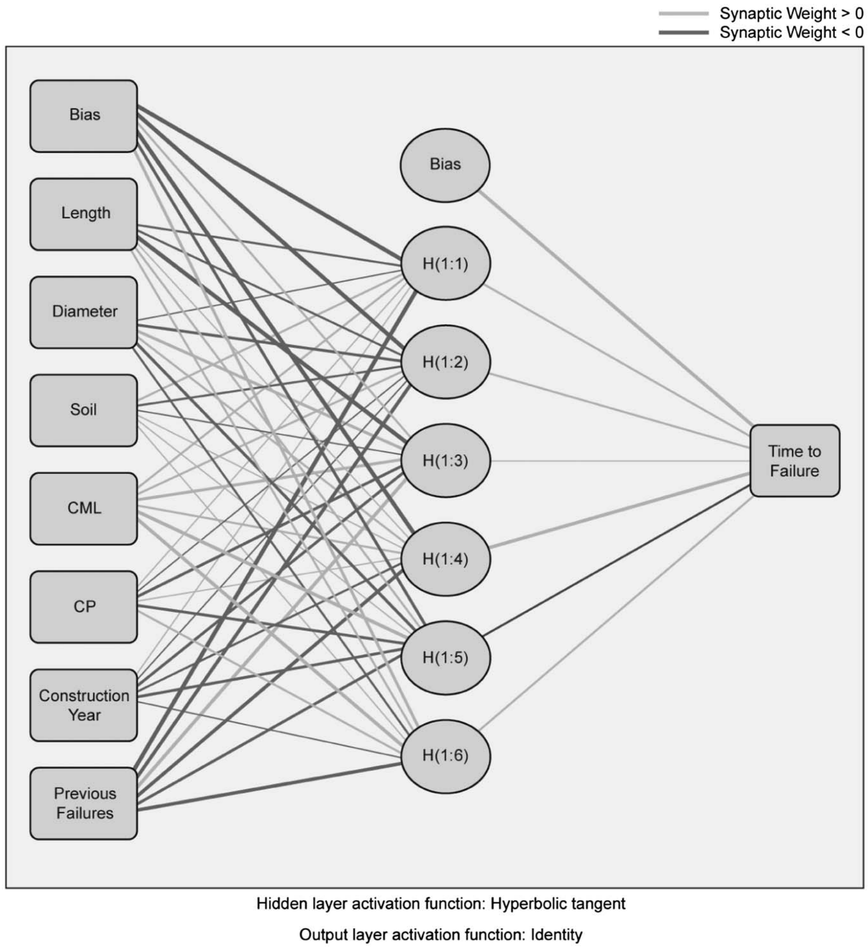

Fig. 4. Optimized cast iron artificial neural network architecture

The ANN best-suited for cast iron failure prediction consisted of seven input nodes (length, diameter, soil, CML, CP, year of construction, and number of previous failures) and six hidden neurons. The architecture of the model is provided in Fig. 4, where thick lines between neurons indicate a strong connection. The correlation coefficient for the 1,169 instances in the holdout set was 0.70.

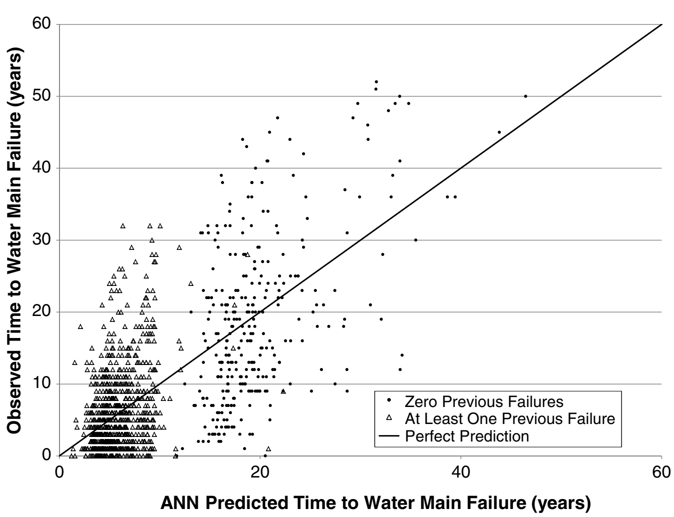

Fig. 5. Scatterplot of cast iron artificial neural network predictions of the time to failure

The scatterplot of the observed versus predicted time to failure in Fig. 5 shows that while the network is not perfect in its predictions, it is capable of providing a reasonable estimate of the observed time to failure based on attribute information available for training. Fig. 6 illustrates the difference between the observed and predicted times to failure in the holdout set. The average absolute value of the difference between observed and predicted time to failure for instances in the holdout set with 0 previous failures, 1 previous failure, and at least 2 previous failures are 8.2, 6.1, and 3.5 years, respectively.

The optimal ductile iron ANN architecture consisted of seven input nodes (length, diameter, soil, CML, CP, year of construction, and number of previous failures) and four hidden neurons. The correlation coefficient for the 218 instances in the holdout dataset was 0.81, which is the highest of all three ANNs and indicates the model is capable of providing a reasonable estimate of the time to failure for the 1,747 ductile iron water mains in Scarborough.

Discussion

Planning Future Rehabilitation Activities

The predictive performance of the developed neural networks indicates they have learned to provide a reasonable estimate of the time to failure for an individual pipe given a set of pipe-specific attributes. As such, predictions of the timing of future failure for an individual pipe can be made if that pipe has similar attributes to

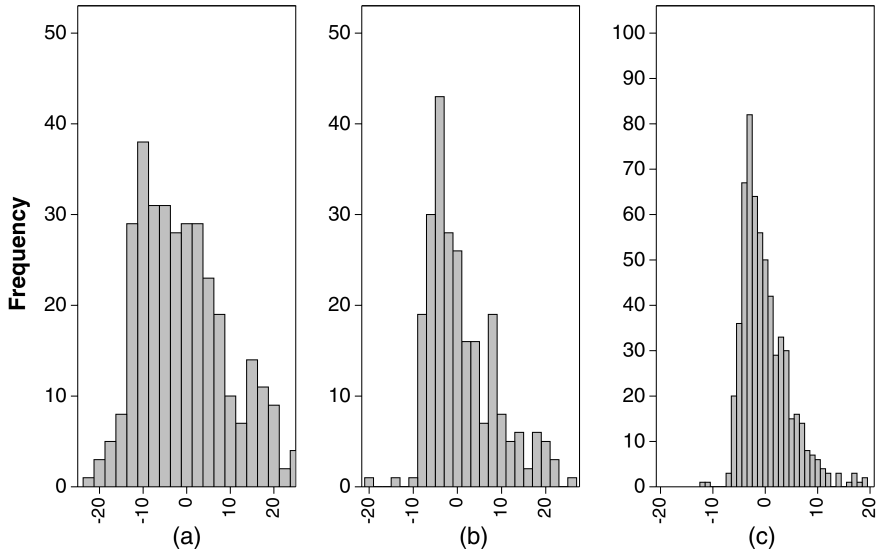

Fig. 6. Histogram of the difference between observed and predicted time to failure for cast iron watermains with (a) zero previous failures, (b) one previous failure, (c) two or more previous failures

instances used to train the neural network. Consider a cast-iron water main installed in 1961, with a length of 52 m, diameter of 150 mm, buried in silt/clay, and one previous break in 2005. Presenting this information to the asbestos cement ANN results in a predicted time to failure of 10 years. Because the first failure occurred in 2005, this second failure is expected to occur in 2015.

The ANN can be used to iteratively predict the timing of failures 1 through 10 for pipes in the distribution system. As an example, Fig. 7 illustrates the predicted number of future failures for the 1,528 cast-iron water mains installed post-1946 that were left without CML or CP as of 2005. Historical records indicate the total number of pipe failures for all pipes in 2005 was 117 (after approximately half the pipes in the distribution system were protected by CML or CP). Simulations obtained from the cast iron ANN indicate the number of annual failures solely for this subset of pipes left unprotected will likely be in the range of 300 per year by 2015 with more than 50 cast-iron pipes per year reaching 10 total failures. While predictions of the year of future failure for some pipes in the distribution system predate 2006 (a contradiction to the historical dataset of observed failure that indicates the failure in question had not yet happened as of 2006), the ANN has based its prediction on what was learned about the time to a failure from other similar pipes that actually failed. In other words, if a prediction is to be made for a pipe with two recorded failures, the predicted time to the third failure will be based on what was learned from other similar pipes with an observed time between second and

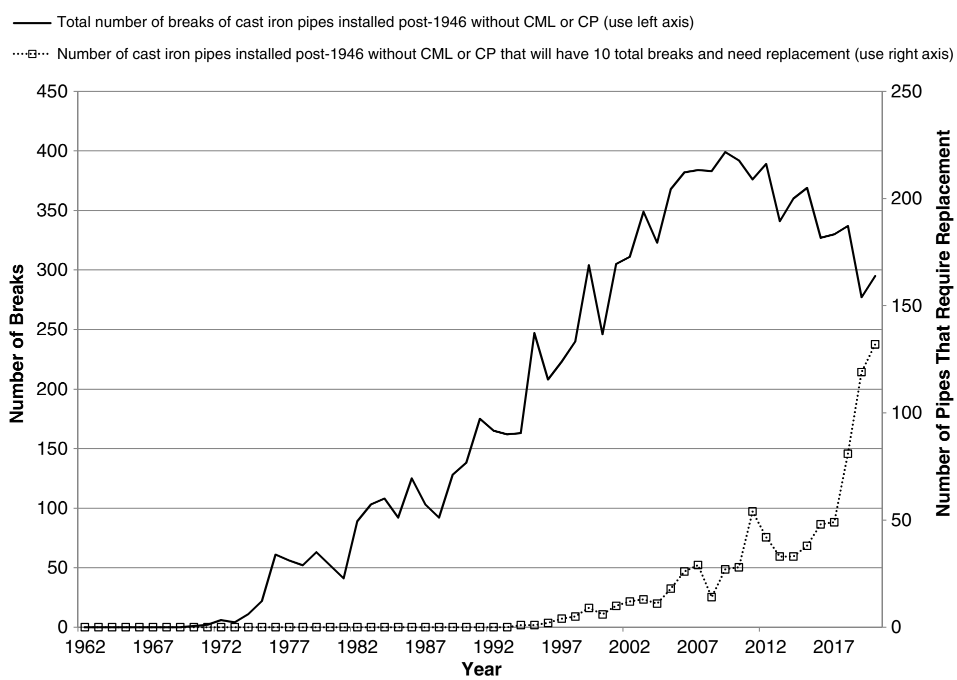

Fig. 7. Predicted number of yearly failures for cast-iron pipes installed post-1946 without CML or CP

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Table 4. Independent Variable Importance Analysis

Attribute	Asbestos cement ANN		Cast iron ANN		Ductile iron ANN	
	Importance	Normalized importance (%)	Importance	Normalized importance (%)	Importance	Normalized importance (%)
Soil	0.051	11.7	0.025	7.9	0.024	7.2
Length	0.051	11.8	0.071	22.5	0.049	14.8
Diameter	0.149	34.4	0.132	41.8	0.074	22.2
Construction year	0.316	73.0	0.136	43.1	0.103	30.8
CML	—	—	0.186	58.7	0.282	84.6
CP	—	—	0.133	42.1	0.135	40.4
Previous failures	0.433	100.0	0.316	100.0	0.333	100.0

third failure. While there is some uncertainty in prediction, each network provides reasonable estimates of failure, so predicted failures predating 2006 should not be dismissed as being inaccurate. Rather, pipes with predicted failures predating 2006 should become candidates for inspection as historical records indicate other similar pipes have already failed. These simulations and the knowledge learned from earlier discussions about the positive impact of CML and CP on reducing annual failures in Scarborough indicate CML and CP installation should be carried out for all unprotected candidate pipes to prevent escalation of future failure rates.

While the neural networks are capable of providing a realistic estimate of the time to failure for individual pipes, each prediction is an expected value that should not be used as a stand-alone number for rehabilitation decision making. Rather, the predictions are more suited to supplementing information learned from existing records of failure and other failure-related predictions (i.e., predicted failure rates, condition scores, or total number of failures) so that a more complete understanding of individualized pipe failure behavior is made available for inspection and rehabilitation decision making. While predictions obtained through statistics or data mining approaches cannot be used to identify where along the length of the pipe failure will occur, each candidate for rehabilitation can be inspected using state-of-the-art, free-swimming acoustic sensors that are now widely available. Capable of inspecting live pipelines up to 25 km long, this technology can be used to identify the location of existing leaks before they become catastrophic failures (Pure Technologies 2012). Inspection results from these in-line surveys can be used to determine if rehabilitation (i.e., cured-in-place pipe installation) or replacement actions need to be carried out for those water mains predicted to fail.

The Influence of Pipe-Specific Attributes on ANN Prediction

The modeling software was used to carry out an independent variable importance analysis to evaluate the influence of each attribute on the output of the trained models (Table 4). The number of previous failures had the greatest influence on prediction for all three models [consistent with Goulter and Kazemi (1988), Sundahl (1997), and Asnaashari et al. (2013), where failure history strongly influenced failure behavior over time]. Predictions provided by the asbestos cement model were largely influenced by the number of previous failures, the year of construction, and pipe diameter. While variations in CML and CP protection strongly influenced the predicted time to failure in the cast iron and ductile iron models, the introduction of soil type as an attribute within the model was shown to be largely irrelevant. The available division into either sand/gravel or silt/clay appears to be insufficient and specific information on the resistivity and corrosivity of the soils should be collected before the influence of soil on failure behavior can be fully evaluated.

The developed neural networks rely on a set of basic attributes when predicting the time to failure for an individual water main, and it is likely that predictive performance could be improved if additional data were made available for model development. Future work in predicting failure should aim to include information on pipe location within the regional area if it is available, as water infrastructure is now commonly spatially integrated with maps of other municipal infrastructure assets (i.e., roadways and sewer lines). The sensitivity of modeling accuracy to variations in available failure history (i.e., failure records dating back 10 years versus 20 years) is an additional area of research that merits investigation. Others looking to carry-out time to failure modeling should aim to include pipe wall thickness and water pressure information data, if available, as both are known to be important factors controlling leakage and break potential (Skipworth et al. 2002).

As indicated in this research, pipe failures in Scarborough are highly seasonal, and failure in winter is likely attributed to the generation of circumferential pressure that develops as temperatures drop below 0°C causing the soil around the pipe to freeze and expand. The penetration of the frost layer deep into the soil during the coldest months and the formation of ice lenses may cause additional frost heave pressure (C-SHRP 2000). Stress caused by the binding action of ice at the boundary between pipes and freezing soil may induce additional longitudinal strain in the pipe (Kim et al. 2005). Pipe failures during the early stages of the spring thaw (March) are likely the result of reduced load support caused by a temporary saturation of the soil surrounding the pipe that occurs as the frost layer melts. Specific burial depth information for each pipe in Scarborough was not available for analysis at the time of this research, and an evaluation of the influence of burial depth on failure is merited if depth information is made available in the future.

Incorporation of temperature data (winter severity) may also improve predictive accuracy of the neural networks. The influence of temperature-based covariates on predicted time to failure may prove to be pipe-material-specific, as temperature has previously been found to have more of an impact on the total number of pipe failures for subsets of cast-iron water mains than ductile-iron water mains in Scarborough (Rajani et al. 2012). Temperature covariates were less related to the total number of ductile-iron pipe failures, as this material fails more from the impact of perforations in the pipe wall induced by corrosion than fracture induced by temperature change.

Conclusions

An analysis of historical water main failures in Scarborough, Ontario, Canada, illustrates the merits of cement mortar lining

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and cathodic protection installation practices for controlling deterioration in aging water distribution pipes. The installation of CML and CP reduced the number of annual water main failures from more than 300 in the mid-1980s (before installation) to less than 150 in 2005, which is approximately equal to the number of annual failures in the mid-1960s when the distribution system was half of its current size. CML and CP reduced the number of days in a year with multiple failures occurring at different locations in the distribution system from approximately 100 in the mid-1980s to 30 in 2005.

Water main failures in Scarborough were found to be strongly influenced by seasonal changes, with approximately 60% of all failures occurring from November to February. Winter pipe failures are likely influenced by the frost layer, as it penetrates deep into the soil during colder months, and an investigation into the influence of temperature (winter severity) on time to failure appears to be warranted.

Neural network models developed in this research can be used to predict the time to failure for individual water mains using commonly recorded pipe attributes. Networks were trained using the online back-propagation with momentum algorithm and a double-loop technique that determined optimum ANN architectures from the wide variety of possible network configurations. Unique models were developed for asbestos cement, cast-iron, and ductile-iron water mains. Performance of the networks for instances reserved for evaluation indicate acceptable prediction capabilities (correlation coefficient of 0.70 for 37 asbestos cement instances, 0.70 for 1,169 cast-iron instances, and 0.81 for 218 ductile-iron instances). The predicted time to failure can be used to determine the year of failure, and this can in turn be used to help guide inspection-related decisions for individual pipes in the distribution system. Simulations of future failure for pipes left unprotected by CML and CP indicate a return to the elevated failure rates of the mid-1980s if pipe protection practices are not extended to include all candidate pipes in the distribution system. The installation of CML and CP would extend the life span of aging water mains in the regional area, and continued implementation would help maintain distribution system reliability. Adequate investment into this aging infrastructure would ensure reliable access to safe drinking water, create jobs, recapture revenue lost from leaking water, and enhance North America's economic competitiveness for years to come.

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