Using Water Main Break Data to Improve Asset Management for Small and Medium Utilities: District of Maple Ridge, B.C.

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Abstract: An approach is developed for identifying key data to be used in asset management in general, and for predicting pipe breaks and selecting appropriate models in particular. The approach is applied to the District of Maple Ridge, B.C., Canada to identify the magnitude of a utility's pipe burst problems today and in the future, enhance the development of pipe replacement priorities based on forecasted breaks, and identify key data to collect in future data acquisition programs. It may also be used by other utilities with varying amounts of data, and can be easily implemented with existing data management and analysis tools.

Introduction

Water utilities have aging and deteriorating infrastructure and must prioritize the replacement of their water mains to minimize pipe breaks. Breaks result in loss of water to key businesses and critical facilities, may lead to damage of other infrastructure, and have been identified as a pathway for microbial contamination of distribution systems (USEPA 2002). The need for rehabilitating aging water mains is increasing, the costs of repairs and replacement can be high, and the impact on customers potentially significant (USEPA 2001). Asset management practices are generally used to prioritize pipe replacements and thereby identify investment strategies that, on one hand, avoid premature replacement of pipes (i.e., unnecessary preinvestment of funds), and on the other hand, avoid water main breaks, commensurate interruptions in service, and the costs of damage. An effective asset management decision is dependent on the ability to determine the future performance of water mains by predicting water main breaks, and identifying how such breaks may occur.

Much research has focused on the development of models for predicting water main breaks and pipe deterioration, but the use of such models is not common among utilities. In addition, the amount and quality of water main break data available for developing or implementing these models varies among utilities (Wood and Lence 2006). Many utilities are not confident in the data they have and this is generally an impediment to investing in pipe prediction models.

This paper reports on an approach applied to Maple Ridge, B.C. to identify key data to be used in asset management in general and pipe break prediction modeling in specific and to select the most appropriate model for predicting water main breaks. This information may then be used to enhance the development of replacement priorities based on forecasted breaks, the maintenance of the database, and the identification of future data acquisition programs. It provided the utility with a method for considering future pipe breaks in the analysis of pipe prioritization strategies, and it incorporates existing tools for data management and analysis that are widely available and easy to implement by small and medium size utilities. The approach is applicable to utilities with varying amounts of data. The results of the application of the work to the Laity View area of Maple Ridge, B.C. are reported in this paper. The following sections review the available techniques for predicting pipe breaks, the factors that influence break predictions, the approach employed for Maple Ridge to assist in asset management of its pipe networks and the results of the Maple Ridge implementation of the work.

Water Main Breaks

A number of authors analyze and report on the causes of breaks, including O'Day (1982), Marks et al. (1987), Male et al. (1990), Savic and Walters (1999), Rajani and Makar (2000), Rajani and Kleiner (2001), and Dingus et al. (2002). According to Rajani and Tesfamariam (2005), a combination of circumstances leads to pipe failure in most cases and different factors cause failure in different pipe networks. The causes of breaks include deterioration as a result of use (e.g., internal corrosion), physical loads applied to the pipe (e.g., traffic, frost), limited structural resistance of the pipe because of construction practices during installation and declining resistance over time (e.g., corrosion, aging factors). Dingus et al. (2002) note multiple common failure modes for cast iron pipe systems and that corrosion, improper installation, and ground movement are the three most common causes of pipe failure. According to Levelton (2005), corrosion is dependent on a number of factors including material, soil type, chemical characteristics of soil, soil bacteria and stray electrical currents.

Prediction Modeling of Water Main Breaks

Break prediction models have been developed to help the water industry understand how pipes deteriorate and when pipes will

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break in the future. These models are typically grouped into two classes—statistical and physical–mechanical models (Kleiner and Rajani 2001). Statistical models use historical pipe break data to identify break patterns and extrapolation of these patterns to predict future pipe breaks, or degrees of deterioration. Physical–mechanical models predict failure by simulating the physical effects and loads on pipes and the capacity of the pipe to resist failure over time.

Statistical models are typically characterized as either deterministic or probabilistic equations (Kleiner and Rajani 2001). Under the deterministic models, the pipe breakage is estimated based on a fit of pipe breakage data to various time-dependent equations, which may represent the cumulative pipe breaks as a function of time from date of installation or from the earliest date of available break data, and most commonly are time–linear (Kettler and Goulter 1985) or time–exponential functions (see, e.g., Shamir and Howard 1979; Walski 1982, and Kleiner and Rajani 1999). Prior to fitting these functions, pipes are partitioned into groups that have similar characteristics, and the functions are evaluated for these groups. The characteristics used to sort the pipes are based on the factors that are assumed to influence breaks such as pipe age, pipe material, diameter, or soil type. Probabilistic models predict not only the failure potential, but the distribution of failure. These models are more complex than deterministic models and require more data. Examples of these include cohort survival, such as KANEW (Deb et al. 2002), Bayesian diagnostic, break clustering, semi-Markov chain and data filtering methods. Physical–mechanical models typically fall into one of two classes: deterministic models which estimate pipe failure based on simulation of the physical conditions affecting the pipe (Doleac et al. 1980, and Rajani and Makar 2000), or probabilistic models that use a distribution of input conditions, such as rate of corrosion, to predict the likelihood and distribution of pipe failure (Ahammed and Melchers 1994). These models have been developed primarily for cast iron and cement pipes.

Physical models have significant data needs. Kleiner and Rajani (2001) suggest that only larger diameter mains with costly consequences of failure may justify the required data collection efforts for these models, and that statistical models based on fewer data may be used to gain insights for future performance. Because the literature suggests that breaks and causes of breaks for any particular water distribution network are system specific (Rajani and Tesfamariam 2005), a utility must create its system specific model based on the deterioration factors that are relevant for the utility. Small and medium utilities typically have the capacity to use statistical deterministic models, but the implementation of physical models is not practical due to the data collection efforts and model maintenance required. For these utilities, it is often most important to gain insights about the rate of pipe breakage, that is, whether the quantity of expected breaks is increasing linearly or exponentially.

Factors for Predicting Water Main Breaks

A number of studies identify factors for predicting water main breaks, although the relevance of the data appears to be specific to the system investigated. O'Day (1982) reviews break studies in Manhattan and Binghamton, N. Y., and cites a number of studies that use age as an indicator for predicting break rates for cast iron pipes. He notes, however, that age alone is a poor predictor of main break patterns and identifies the major determinants of water main break rates, as localized factors such as corrosion conditions, construction practices, and external loads. He also finds that

soil type affects external forces on water mains, such as shrink–swell, frost penetration, and external corrosion. According to Jacobs and Karney (1994), pipe age range is an effective basis for models because pipes of a given age range are typically uniform with respect to manufacture, installation and to a large extent, operating conditions. Moreover, pipes installed in geographically contiguous sections often share similar soil conditions, installation conditions, and pressure regimes. In their study, Jacobs and Karney group pipes based on material, diameter, and fairly broad age ranges and develop regression relationships for pipe breakage versus age and versus pipe length. Savic and Walters (1999) suggest that the causes of water main failures may be split into quality, age, type of environment, quality of construction workmanship, and service condition and find that age, length, and diameter are the most important variables in influencing pipe bursts. Kettler and Goulter (1985) find that break rate, age, and material are related for asbestos cement and cast iron pipes. In their study, no single failure type of asbestos cement pipes exhibited a marked change in the rate of failure with time, and there were distinct changes in the failure rate with time for some types of failure in cast iron pipes. According to Male et al. (1990), different manufacturing processes of cast iron pipes can account for differences in durability. Cooper et al. (2000) apply a probabilistic approach to estimate trunk main failure probability, based on four key variables: number of buses per hour, pipe diameter, soil corrosivity, and density of pipes in a given area. They find that pipe age and material are important factors contributing to the break probability. Rajani and Tesfamariam (2005) show that long-term performance of buried cast iron is dictated by pit growth rate, unsupported length, fracture toughness, and temperature differential.

Data typically used in models are surrogates for factors that can explain breaks. For example, as shown in Table 1, the age of a pipe may represent the method of pipe manufacture or particular construction standards, as well as deterioration over time. Bedding material may be an indicator of a particular construction practice that induces physical stress, of the structural resistance of the pipe, or of the soil type. For example, in some utilities where native soil is used as backfill, the soil may not be screened for rocks and other objects or properly leveled. As a result, this construction practice results in circumstances where a stress is induced on pipes and ultimately causes failures. In some cases, fines migration of corrosive native soil through particular bedding types can occur and create the potential for external corrosion. Soil type can represent corrosivity and potential for external pipe corrosion, which is also dependent on the pipe material.

Availability of Water Main Data

The amount of water main break data needed for extensive model development is not commonly available in many utilities (Wood and Lence 2006), in spite of best practices recommended by the *National Guide to Sustainable Municipal Infrastructure* (NGSMI 2002) and AWWARF (Deb et al. 2002). Most municipalities only have limited recorded pipe breakage histories and do not have much data for analysis (Pelletier et al. 2003). However, in many instances utilities may have more data than they realize. They can apply approaches such as "webbing" or linking available data from archives, models, and other such sources (Wood and Lence 2006) to construct databases for analysis.

A key to any data management strategy is identifying the purpose for which one is collecting and analyzing the data, whether it is for asset management, compiling an inventory of assets or discovering the magnitude and nature of pipe breaks. There is grow-

Table 1. Typical Data Used in Models and Factors for Which They Are a Surrogate

Surrogate	Factor
Age	Method of pipe manufacture, construction standards, deterioration over time
Pipe material	Construction practices, method of manufacture, failure mechanisms and causes, joint failures
Pipe diameter	Wall thickness and resistance to beam loading, pipe use, method of pipe manufacture, construction standards
Type of pipe lining	Method of pipe manufacture, resistance to corrosion
Bedding and backfill material	Physical stress on pipes caused by construction practices, structural resistance, soil type, fines migration
Pipe protection (wrapped/anodes)	Structural resistance, life expectancy, construction practices, method of pipe manufacture
Pipe condition	Remaining life
Soil type	Soil corrosivity, physical loading on the pipe such as swelling and frost, level of pipe protection, ground water effects such as draining ability or corrosion, construction practices, bedding and/or backfill material
Under a boulevard or roadway	Physical loading from surface loads such as traffic, road salt effects
Depth of cover	Physical loading on the pipe from the weight of soil
Surface material/type	Physical loading from surface use
Normal operating pressure	Internal pressure on pipe structure
Typical flow in area of break	Physical impact from factors such as accelerated internal corrosion from low flow mains, water hammer effects
Traffic classification	Physical loading from surface loads such as traffic volumes and wheel loads
Road/surface usage	Physical loading from surface loads

ing interest in using knowledge discovery techniques such as data mining for water main break data (Savic and Walters 1999). Knowledge discovery is the process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data (Torra et al. 2004). Such patterns may help to identify factors that are related to breaks. If a utility has sufficient data and the requisite skill and ability, it may be able to apply such knowledge discovery techniques to detect patterns, although for most utilities, rudimentary statistical analyses by technical staff are sufficient for detecting patterns in their data, as is demonstrated in this paper.

Using Prediction Models to Improve Asset Management

The approach applied to Maple Ridge, B.C. is presented herein. The approach may be used to guide a utility in identifying the magnitude of its water main break problems today and in the future, and thereby enhance the development of strategies for prioritizing pipe replacements and data collection. Its salient feature is that it integrates break prediction or deterioration models that provide an indication of future pipe conditions with existing data, and thereby uses enhanced estimates of vulnerability for each pipe. It is designed to accommodate systems with limited data but is sufficiently flexible to adapt for additional information that may be acquired over time. Other design considerations include ease and transparency of use and facilitation of a decision-making process that is repeatable and defensible.

Traditionally, utilities prioritize pipe replacements based on a combination of current management practices and historical pipe breakage data. Management practices include directives based on general guidelines, consequence assessments, legislative requirements, and other utility priorities. Rudimentary analyses employed interpret historical pipe break data, including location, time, and date of break, and pipe diameter and material, and typically have provided information regarding where and how many breaks are occurring, and what pipes are experiencing breaks

(Kleiner and Rajani 1999). Considering this information, the priority of the utility may be to replace water mains of a certain material or size, those in a certain area due to previous failures, those under roads that are to be repaved, those that are currently undersized, or those that have significant consequences if failures were to occur, such as mains that serve hospitals. Some utilities may use a multiple objective approach, weighting each of a number of prioritization criteria, and assigning points to each pipe that describe the degree to which it meets a given criteria (see Deb et al., 2002; Sargeant 2003).

The approach is shown in Fig. 1. In order to forecast pipe breaks, the historical data set may need to be expanded with data available from other sources within the utility and from external agencies. In addition to historical pipe breakage data, data for factors that may be important for predicting water main breaks as previously described may need to be obtained, including soil type, surface, bedding, and backfill material, type of road usage, or typical flow in area of break. This information may be consolidated by creating a "web" of data, which does not establish a new database per se, but draws from available data for analysis when required, as described by Wood and Lence (2006).

These data may be used directly in the prioritization process and as input to break prediction and deterioration models. The input to the models is developed by grouping pipes in which breaks have occurred based on factors that contribute to breaks. Material and diameter data are available to most utilities and should be considered as the minimum factors on which to base pipe groups. The decision of whether to use a physical–mechanical or statistical break prediction model may be made at this point, because the pipe material determines whether a physical model exists for a given pipe and the diameter influences the practicality of applying such a model. For small and medium size utilities, the practical starting point is deterministic statistical models, which may be developed with readily available commercial software, including spreadsheets. More capable utilities may consider more complex statistical or even physical–mechanical models, however, the long-term use and maintenance of these
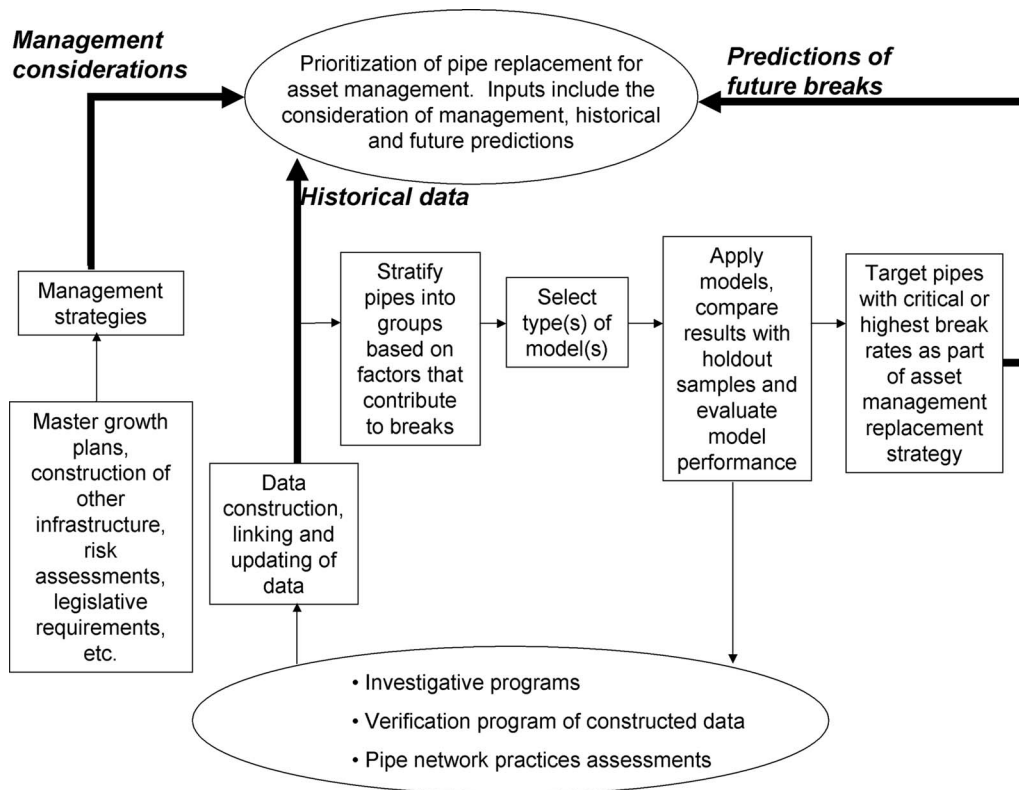
Fig. 1. Improving asset management using pipe break prediction models

models is a serious consideration for those who choose these models.

To evaluate the accuracy of a given statistical model, a portion of the break data should be used to develop the equations and the most recent portion of the break data should be retained as a holdout sample for comparison. For example, if a utility has 20 years of break history, it may choose to develop models based on the first 15 years of data, and compare the model predictions with the remaining 5 years of actual breaks to assess the accuracy of the predictive model. Although 5 years is a reasonable length of holdout sample, this is a function of the length of record, and data required to generate the statistical models.

In developing and using statistical models, one must determine the amount of data that are required, the level of detail to be modeled, and the knowledge that will be gained. In order to determine the length of record required to develop a credible statistical model, the pipe break record used to model the system may be varied to evaluate the sensitivity of the model accuracy to the length of record used.

In order to evaluate the important factors for predicting pipe breaks, the pipe break data may be subdivided into different subgroups and models for each of these subgroups may be developed and compared in terms of their relative accuracy. This process naturally reduces the number of breaks within each subgroup used in performing statistical analyses, but may yield more credible models. Considering data that are typically available to utilities (Wood and Lence 2006), potential subgroups of pipes include those of a specified (1) pipe material and diameter, which indicate pipe strength; (2) pipe material, diameter, and age, which indicate pipe strength and age effects such as deterioration and construction practices; and (3) pipe material, diameter, soil type, and age, which indicate pipe strength, interaction of the pipe material and the soil, and age effects. Should the utility have access to infor-

mation regarding surface conditions, this may also be considered in forming the pipe subgroups.

The model results will indicate the factors that are important for predicting breaks and the common failure types for a network, and this information may provide insight into pipe deterioration behavior. Based on the model results, managers may target pipes that have the highest predicted breaks or rates of breaks for prioritization and identify the need for future investigative programs such as soil and pipe condition assessments and data acquisition strategies such as changes in field collection practices. The utility may also choose to verify the data or conduct investigative assessments to understand the deterioration of pipes that have significant breaks but cannot be accurately modeled. From these activities, new data can be created to improve the understanding of pipe deterioration factors.

Pipe network management practices may also be altered based on the model results. Examples of such changes include identification of new design specifications such as the type of joints required for certain pipes in a particular soil, and introduction of corrective measures such as cathodic protection programs. In order to maintain relevance, it is recommended that models be routinely reviewed and updated as part of the detailed capital plan of the utility, to account for changes in the rate at which breaks are occurring as a result of the changes in pipe management practices. Finally, break data should be kept current.

Break Prediction Models for Laity View, Maple Ridge, B.C.

The approach was applied to the Laity View area of Maple Ridge, B.C., Canada as a means of screening for key data to collect and assisting in the development of strategies for prioritizing pipe

replacements and data collection. This area comprises 13% of the 335 km distribution system for Maple Ridge, is representative of the urban area, has the same construction practices and soil types found in the rest of the municipality, and serves a population of approximately 6,000. The pipe materials found in the area are asbestos cement, cast iron, ductile iron and steel, and pipe diameters are 150, 200, and 250 mm. Pipe installation records begin in 1959 and few pipes were installed before this date. The soil types found in the Laity View area are clay, silty-clay, silt and sand.

Break data are available from 1983 to 2004. A total of 54 breaks occurred in this period, and seven of these occurred after the year 2000. Four pipes experienced two breaks and one broke three times. This is typical of pipe networks comprised of newer pipes. Preliminary analysis of these data indicates that breaks are occurring in asbestos cement, cast iron and ductile iron pipes, in pipes that are greater than 15 years old, and in clay and silty-clay type soils (Wood et al. 2007).

Given the 20-year history of record, the final 5 years from 2000 to 2004 was selected as the holdout sample. It was observed that increasing the holdout sample's length of time reduces the amount of history and number of recorded breaks available for developing models. As the amount of break history increases, the utility may investigate the effect of a longer holdout sample. In this case, 75% of the length of records was considered to be the appropriate amount of time to use to create models and 25% was used as the holdout sample. As well, 5 years was considered the minimum coarseness of time increment to be used in the development of the time-based pipe break prediction models and also corresponds to the capital planning time periods used by Maple Ridge. The time increment should be carefully selected and utilities may find it useful to plot the number of breaks per year prior to selecting the most representative time increment for observing trends and including an adequate amount of breaks in each incremental time period. This could add bias and should be considered by utility managers. To investigate the important factors for predicting pipe breaks, pipes in the area were grouped based on the four types of subgroups previously described. Information for surface material which includes asphalt, concrete, and gravel or grass, is available for this region and thus a fourth subgrouping was examined that included pipes of a specified pipe material, diameter, age, and surface material.

Pipe age subgroups were created by examining the data and identifying time periods in which a meaningful number of breaks occurred. For asbestos cement and cast iron pipes, these subgroups were comprised of pipes with installation dates before 1959, between 1960 and 1974, and between 1975 and 1984. Asbestos cement and cast iron pipes were not installed in Maple Ridge after 1984. Ductile iron pipes were subgrouped into pipes with installation dates between 1970 and 1979, 1980 and 1989, 1990 and 1999, and subsequent to 1999. The only steel pipes were installed in 1978 and are approximately 24 m in length. These have not broken. Statistical deterministic equations for each group of Laity View pipes were developed for time–linear and time-exponential functions.

The time–linear equations for the cumulative number of breaks at year t are based on

$$N(t) = A(t - t_0) + C \qquad (1)$$

where $N(t)$=cumulative number of breaks for the year t, t_0 =reference year, in the case of Laity View, 1983; A=coefficient; and C=constant.

Time-exponential equations for the cumulative number of breaks at year t are based on

$$N(t) = Ae^{k(t-t_0)} \qquad (2)$$

where A and k=coefficients and all other variables are as described earlier.

For each subgroup which had sufficient data, equations were derived using S-Plus and spreadsheet software to solve for the coefficients. A minimum of two breaks is required in order to estimate these equations, and thus equations could not be derived for all subgroups analyzed. Because there were few breaks in many of the subgroups, it was not realistic to determine the statistical significance of the models and predictions. Instead, recognizing that this approach is part of a long-term process for analyzing and evaluating water main breaks, the accuracy of the predictions was taken as a first approximation of the representativeness of the time increments and the models and the relative accuracy was used to determine the fitness for the equations with respect to the rate of breaks. For each subgrouping, the percent of all pipes for which an equation could be derived was estimated, as this is an indication of the extent of the network that may be modeled. The accuracy of the derived equations, henceforth referred to as models, was calculated as the percent error of model predictions relative to the cumulative breaks in 2004. Finally for time–linear models, R-squared estimates are reported.

Results of Break Prediction Models

The degree of error of the prediction results for both time–linear and time–exponential models for the various subgroups are shown in Figs. 2–6. The different amount of breaks and the rate of breaks among the various groups suggest that there are differences in behavior for deterioration and breakage. For the material subgroups, three subgroups could be modeled using the number of breaks that occurred between 1983 and 1999 (these are reported in parentheses); those for asbestos cement (29 breaks), cast iron (two breaks), and ductile iron pipes (16 breaks) and these represent approximately 100% of the pipe length in the network. As shown in Fig. 2, the time–linear models are more accurate than the time–exponential models for asbestos cement and ductile iron pipes; the percent error for the time–linear models was 29 and 34, and the percent error for the time–exponential models was 210 and 136, for the asbestos cement and ductile iron pipes, respectively. The range of R-squared statistic for all of the time–linear models was 0.81 to 0.92 with an average R-squared value of 0.84. The results for the cast iron pipes indicate that although few breaks have occurred in these pipes they are occurring at an increasing rate.

The accuracy of predictions for material and diameter subgroups is shown in Fig. 3. Here, seven subgroups had a sufficient number of breaks to be modeled and these represent 99% of the pipe length in the network. Again, with the exception of the cast iron pipes, the time–linear models are more accurate than the time–exponential models. Although the most accurate model is the time–linear model for the ductile iron pipe with a diameter of 150 mm, in general the performance of time–linear models for the asbestos cement and ductile iron pipes is similar. The average R-squared statistic for all of the time–linear models was 0.84 and the R-squared value varied from 0.75 to 0.95.

When age was considered, seven subgroups contained sufficient number of breaks to be modeled, and these represent only 56% of the pipe length in the network. As shown in Fig. 4, the accuracy of the time–linear models for ductile iron pipes improved dramatically, indicating that age effects are important in predicting break rates for these pipes, and should be investigated.
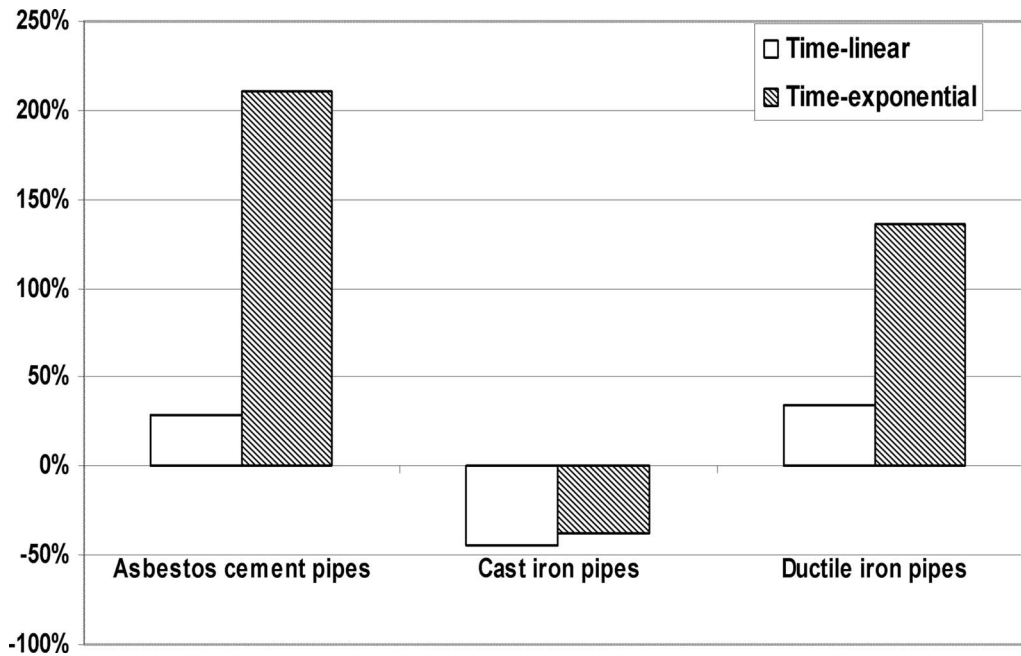
Fig. 2. Percentage of error of time–linear and time–exponential predictions for material groups

With respect to the asbestos cement pipes, the age delineated subgroups suggest that different age groups of 150 mm asbestos cement pipes are behaving differently with respect to breaks, the ability to accurately predict breaks differs, and the number of breaks for pipes installed between 1975 and 1984 are increasing. The R-squared statistic for all of the time–linear models was between 0.75 and 0.94 and the average R-squared statistic was 0.84.

When pipe–soil interactions were considered, eight subgroups could be modeled, but this represented only 38% of the pipe length in the network. The accuracy of predictions for the material, diameter, soil, and age subgroups is shown in Fig. 5. These results suggest that the accuracy of predictions for pipes of the same material differs in different soils, even when they are installed at the same time. When the soil type is considered as a

factor in the analysis, the accuracy of the time–linear models stayed the same or improved relative to analyses that considered only material, diameter, and age. The average R-squared statistic for all of the time–linear models for these subgroupings was 0.78 and ranged between 0.63 and 0.94.

The accuracy of the models for material, diameter, age, and surface material subgroups is shown in Fig. 6. Here, eight subgroups could be modeled but these represent only 40% of the pipe length in the network. Although the average R-squared statistic for all time–linear models for this case was 0.84 and ranged from 0.72 to 0.95, the accuracy of these models is no better than the accuracy of the time–linear models for the material, diameter, and
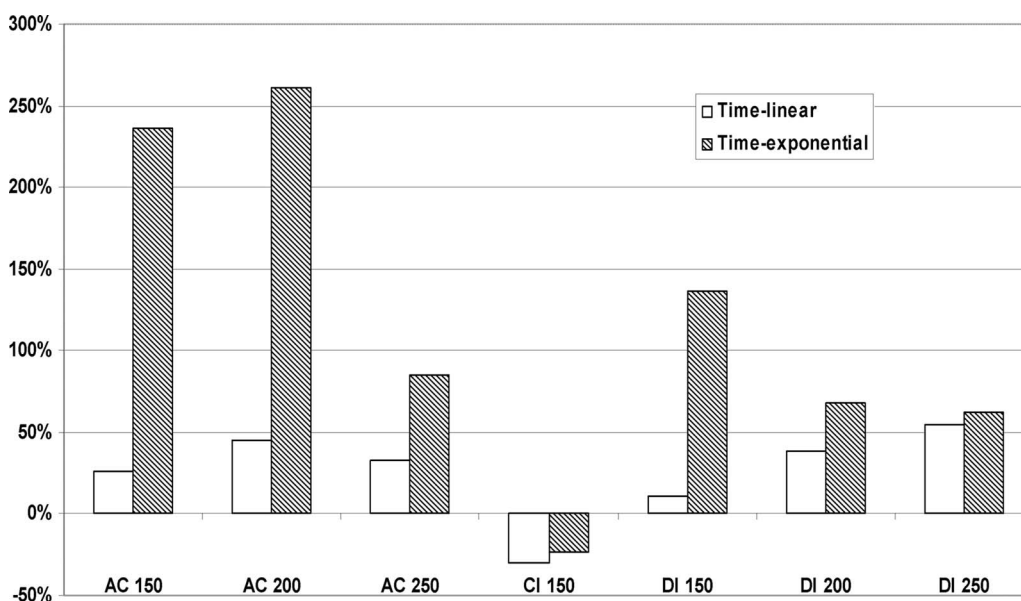

Fig. 3. Percentage of error of time–linear and time–exponential predictions for material and diameter groups
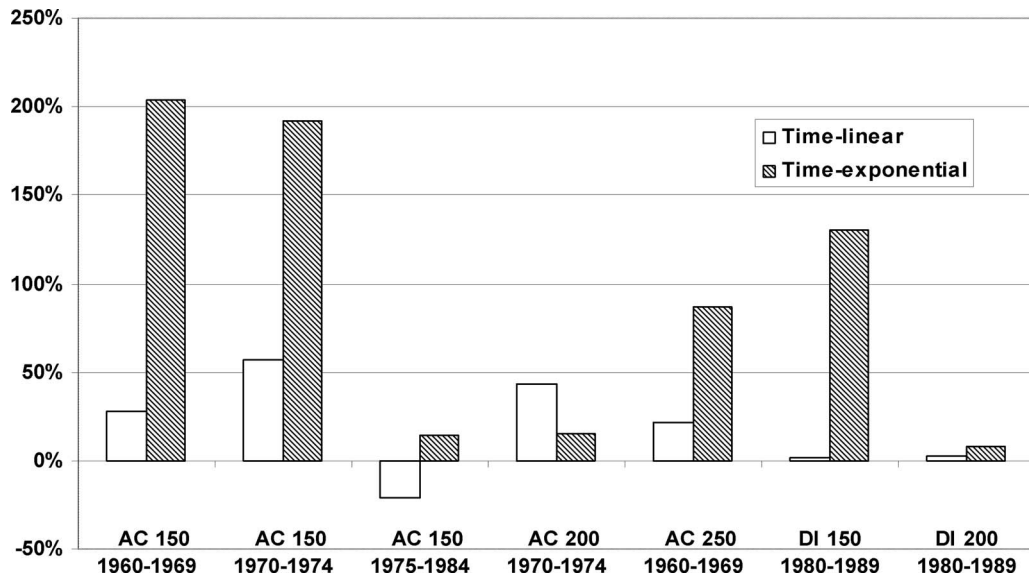
Fig. 4. Percentage of error of time–linear and time–exponential predictions for material, diameter, and age groups

age subgroups alone. This indicates that, in contrast to soil type, surface material may not be an important factor to consider in predicting pipe breaks for Maple Ridge.

For Maple Ridge, the pipe groups associated with models that accurately predict high break rates are: 250 mm diameter asbestos cement pipes installed in clay soil during 1960 and 1969 and 150 mm diameter asbestos cement pipes installed in clay soil during 1970 and 1974. As a result of this analysis, these asbestos cement pipes will be prioritized for replacement. Soil type was also identified as a potentially important factor in modeling breaks because using the soil data to group pipe breaks reduced the degree of model error for many of the pipe groups. Therefore, a subsequent soil sampling program was undertaken to improve the utility's information regarding soil resistivity, pH, chlorides, and soil type. A preliminary pipe sampling program was implemented at the same time to collect information on asbestos cement pipes and ductile iron pipes in the area. As a result of the

sampling programs and observations of installation practices when pipes were exposed during the sampling program, the importance of bedding and backfilling practices and construction inspections was identified by staff and changes in construction specifications and inspection practices are being developed. Plans are under way to apply this approach to the rest of the Maple Ridge network. Ultimately, scheduling of the pipe replacements and budget estimates will be undertaken in conjunction with other management considerations such as road rehabilitation.

An ongoing problem for utility managers is the allocation of scarce resources for both data collection and analysis. One undertaking for determining the value of the approach applied herein and a supporting data collection program is to evaluate the value of the additional information obtained. The value of additional information may be estimated by comparing the decision that would be undertaken without the additional information with the decision that would be undertaken with the additional information
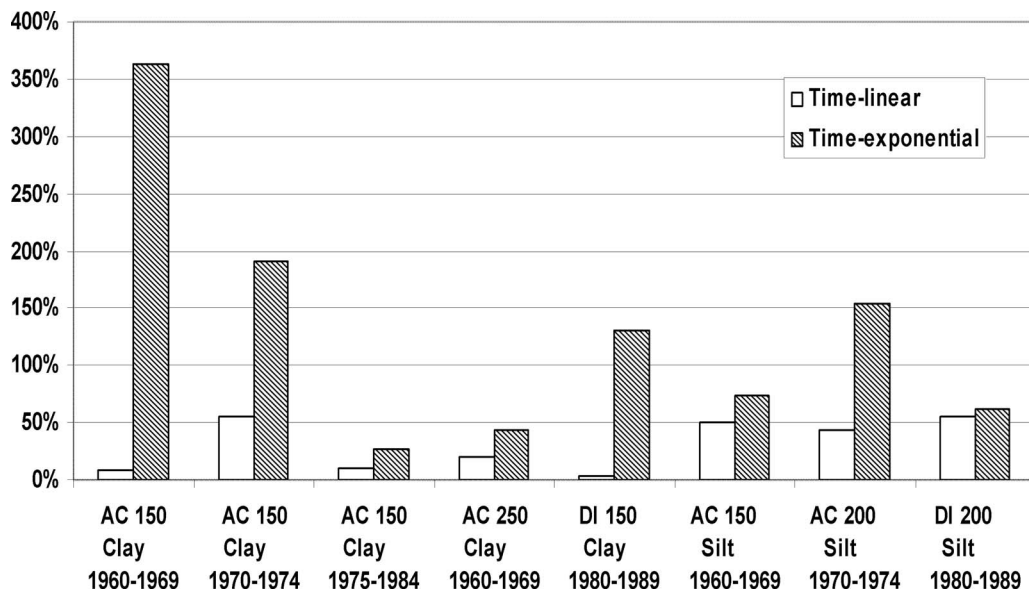

Fig. 5. Percentage of error of time–linear and time–exponential predictions for material, diameter, soil, and age groups

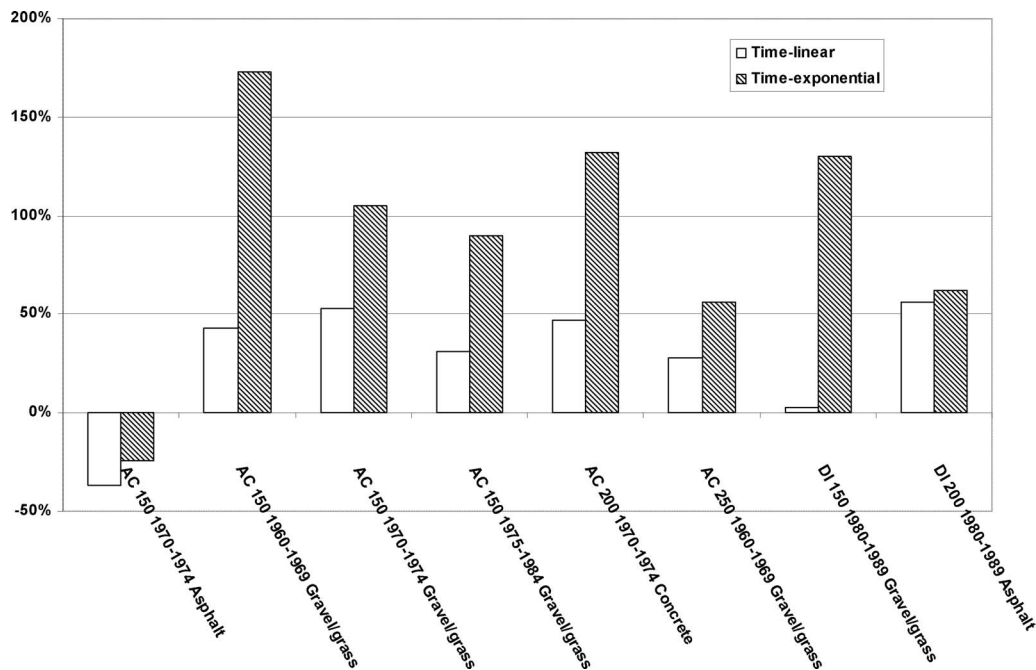JOURNAL OF INFRASTRUCTURE SYSTEMS © ASCE / JUNE 2009 / **117**

Fig. 6. Percentage of error of time–linear and time–exponential predictions for material, diameter, age, and surface material groups

(Schuyler 2001). For example, for Laity View, the value of developing statistical models that incorporate soil data may be determined by comparing the cost of replacing the group of pipes that has the highest break rates based on data for material, diameter, and age (i.e., 250 mm diameter asbestos cement pipes) with that of a replacement strategy that considers replacing only those 250 mm diameter asbestos cement pipes in clay soils. If all 250 mm diameter asbestos cement pipes, with a total length of 646 m were to be replaced, the total cost of replacement would be $193,800 (assuming a replacement cost of $300 /m). Using the methodology it was determined that all the breaks in these pipes occurred in clay soil. If it is assumed that all future breaks of this pipe type will occur in clay soils, replacement of these pipes, with a total length of only 258 m would cost $77,400. Thus the value of the analysis and the soil information is approximately $193,800−$77,400=$116,400. Although this additional information may not always lead to savings in terms of reducing the cost of pipe replacement, for example in cases where all pipes of a certain material, diameter, and age were installed in the same soil type, the information regarding soil type may still be of benefit. This information could be used to improve the installation practices or justify corrective measures.

Conclusions

Predictive modeling is useful for identifying replacement needs over time. However, utilities do not commonly use predictive modeling as part of their asset management practices. There are no common databases for break analysis or common condition indices, and few utilities undertake condition assessment (Grigg 2004), all of which hinders industry-wide use of predictive modeling. The approach used for Maple Ridge improves upon the traditional pipe prioritization approaches that only look at the past history in aggregate and do not necessarily take into account trends and timing of future breaks. An advantage of the approach is that it can be applied by small to medium size utilities with limited information and commonly used analytical tools. For example, for Maple Ridge, although useful information was gained by investigating soil type, reasonable insights may have been drawn from analyses that considered only material, diameter, and age, information that is typically available to most utilities. At the same time, the methodology is flexible and allows for consideration of any available data. In addition to guiding water main replacements, the framework may also be used to identify the key data for predicting water main breaks.

Because there is variability in the causes of pipe breaks among different utilities, in order to understand the performance of their system, utilities should collect data as identified in recommended Best Practices; see NGSMI (2002) and Deb et al. (2002). Additional information may often be obtained efficiently at the time of the break repair by revising forms to collect more information, such as bedding or backfill material (see Wood and Lence 2006). Training will often be required, and it is prudent to verify data. Convincing staff to collect data may be an obstacle, but involving them in decision making can be a way to gain support. By using models to predict future breaks, reviewing the accuracy of the predictions, and updating the models, a utility can improve its asset management practices.

Acknowledgments

References

Ahammed, M., and Melchers, R. E. (1994). "Reliability of underground pipelines subjected to corrosion." *J. Transp. Eng.*, 120(6), 989–1003.

Cooper, N. R., et al. (2000). "The use of GIS to develop a probability-based trunk mains burst risk model." *Urban Water*, 2(2), 97–103.

Deb, A. R., et al. (2002). *Prioritizing water main replacement and rehabilitation*, AWWA Research Foundation, Denver.

Dingus, M., Haven, J., and Russell, A. (2002). *Nondestructive, noninvasive assessment of underground pipelines*, AWWA Research Foundation, Denver.

Doleac, M. L., Lackey, S. L., and Bratton, G. N. (1980). "Prediction of time-to-failure for buried cast iron pipe." *Proc., American Water Works Association Annual Conf.*, AWWA, Denver.

Grigg, N. S. (2004). *Assessment and renewal of water distribution systems*, AWWA Research Foundation, Denver.

Jacobs, P., and Karney, B. (1994). "GIS development with application to cast iron water main breakage rates." *2nd Int. Conf. on Water Pipeline Systems*, Mechanical Engineering Publications Limited, London, 53–62.

Kettler, A. J., and Goulter, I. C. (1985). "An analysis of pipe breakage in urban water distribution networks." *Can. J. Civ. Eng.*, 12(2), 286–293.

Kleiner, Y., and Rajani, B. B. (1999). "Using limited data to assess future needs." *J. Am. Water Works Assoc.*, 91(7), 47–62.

Kleiner, Y., and Rajani, B. B. (2001). "Comprehensive review of structural deterioration of water mains: Statistical models." *Urban Water*, 3(3), 131–150.

Levelton Consultants Ltd. (2005). "Maple Ridge water works corrosion investigation." *Rep. No. 2705-0380*, Surrey, B.C.

Male, J. W., Walski, T., and Slutsky, A. H. (1990). "Analyzing water main replacement policies." *J. Water Resour. Plann. Manage.*, 116(3), 362–374.

Marks, D. H., Andreou, S., Jeffrey, L., Park, C., and Zaslavsky, A. (1987). *Statistical models for water main failures*, U. S. Environmental Protection Agency Water Engineering Research Lab., Cincinnati.

National Guide to Sustainable Municipal Infrastructure—Infraguide (NGSMI). (2002). "Deterioration and inspection of water distribution systems." *Infraguide—Potable Water*, Ottawa.

O'Day, D. K. (1982). "Organizing and analyzing leak and break data for making main replacement decisions." *J. Am. Water Works Assoc.*, 74(11), 588–594.

Pelletier, G., Mailhot, A., and Villeneuve, J.-P. (2003). "Modeling water pipe breaks—Three case studies." *J. Water Resour. Plann. Manage.*, 129(2), 115–123.

Rajani, B. B., and Kleiner, Y. (2001). "Comprehensive review of structural deterioration of water mains: Physically based models." *Urban Water*, 3(3), 151–164.

Rajani, B. B., and Makar, J. (2000). "A methodology to estimate remaining service life of grey cast iron water mains." *Can. J. Civ. Eng.*, 27(6), 1259–1272.

Rajani, B. B., and Tesfamariam, S. (2005). "Estimating time to failure of ageing cast iron water mains under uncertainties." *Water management for the 21st century*, Univ. of Exeter, Exeter, U.K., 1–7.

Sargeant, D. (2003). "Water main rehabilitation prioritization." *American Water Works Association 2003 Seminar—Infrastructure: Above and Below Ground*, AWWA, Denver.

Savic, D. A., and Walters, G. A. (1999). "Hydroinformatics, data mining and maintenance of UK water networks." *Anti-Corros. Methods Mater.*, 46(6), 415–425.

Schuyler, J. (2001). *Risk and decision analysis in projects*, Project Management Institute, Newtown Square, Pa.

Shamir, U., and Howard, C. (1979). "An analytic approach to scheduling pipe replacement." *J. Am. Water Works Assoc.*, 71(5), 248–258.

Torra, V., Domingo-Ferrer, J., and Torres, A. (2004). "Data mining methods for linking data coming from several sources." *3rd Joint Un/ECE-Eurostat Work Session on Statistical Data Confidentiality, Monographs in Official Statistics*, Office for Official Publications of the European Communities, Luxemburg, 143–150.

USEPA. (2001). "Drinking water infrastructure needs survey." *Second Rep. to Congress*, Office of Water, Washington, D.C.

USEPA. (2002). *New or repaired water mains*, Office of Water, Washington, D.C., ⟨http://www.epa.gov/safewater/disinfection/tcr/pdfs/whitepaper_tcr_watermains.pdf.⟩ (Aug. 15, 2007).

Walski, T. M. (1982). "Economic analysis of water main breaks." *J. Water Resour. Plng. and Mgmt. Div.*, 108(3), 296–308.

Wood, A., and Lence, B. J. (2006). "Assessment of water main break data for asset management." *J. Am. Water Works Assoc.*, 98(7), 76–86.

Wood, A., Lence, B. J., and Liu, W. (2007). "Constructing water main break data for asset management." *J. Am. Water Works Assoc.*, 99(1), 52–65.