Journal of Zhejiang University-SCIENCE A (Applied Physics & Engineering)
ISSN 1673-565X (Print); ISSN 1862-1775 (Online)
www.zju.edu.cn/jzus; www.springerlink.com
E-mail: jzus@zju.edu.cn

An assessment model of water pipe condition using Bayesian inference*

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Received Oct. 1, 2009; Revision accepted Apr. 9, 2010; Crosschecked June 10, 2010

Abstract: An accurate understanding of the condition of a pipe is important for maintaining acceptable levels of service and providing appropriate strategies for maintenance and rehabilitation in water supply systems. Many factors contribute to pipe deterioration. To consolidate information on these factors to assess the condition of water pipes, this study employed a new approach based on Bayesian configuration against pipe condition to generate factor weights. Ten pipe factors from three pipe materials (cast iron, ductile cast iron and steel) were used in this study. The factors included size, age, inner coating, outer coating, soil condition, bedding condition, trench depth, electrical recharge, the number of road lanes, material, and operational pressure. To address identification problems that arise when switching from pipe factor information to actual pipe condition, informative prior factor weight distribution based on the literature and previous knowledge of water pipe assessment was used. The influence of each factor on the results of pipe assessment was estimated. Results suggested that factors that with smaller weight values or with weights having relative stable posterior means and narrow uncertainty bounds, would have less influence on pipe conditions. The model was the most sensitive to variations of pipe age. Using numerical experiments of different factor combinations, a simplified model, excluding factors such as trench depth, electrical recharge, and the number of road lanes, is provided. The proposed Bayesian inference approach provides a more reliable assessment of pipe deterioration.

Key words: Bayesian inference, Condition assessment, Pipe factor, Water distribution system, Weight
doi:10.1631/jzus.A0900628 **Document code:** A **CLC number:** TU991

1 Introduction

Water supply systems are very important for human life, especially in populated and congested urban areas (Koo and Ariaratnam, 2006). Typically, the water distribution networks are typically the most expensive component of these systems, and deteriorate gradually due to environmental and operational stresses (Kleiner *et al*., 2001). Nowadays, many countries face the task of maintenance or rehabilitation of the deteriorated water pipes. In a recent study, the American Society of Civil Engineers (ASCE) graded the overall water system in the U.S. with a failing grade of "D−" (American Society of Civil Engineers, 2009). Hence, pipe condition assessment is necessary for proper reinvestment planning to improve the health of the pipes and to provide effective continuous service. Pipe assessment is an essential part in the management and decision-making process of water utilities and has been one of the hottest topics in the water industry in the past decades (Grigg, 2004).

Pipe conditions can be characterized by condition factors and relative weights of the factors (Arun and Yakir, 1995). Having established weights for each factor, a total score is calculated for each pipe by summing the individual factor weights (Rogers and

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* Project supported by the National Construction of High-Quality University Projects of Graduate (No. 2008102915), the National Specially Major Fund of Water Pollution Control and Management (No. 2008ZX07314-005), and the Tianjin Science and Technology Support Program (No. 09ZCGYSF00600), China

Grigg, 2009). The use of condition factors and benchmarking techniques has become a common method (Enrique and Miguel, 2008). "Condition factors" have been one of the greatest interests in the area of water transmission and distribution systems (Alegre *et al*., 2009). However, in the early 1990s, even the International Water Supply Association (IWSA) failed to receive papers on this topic in one of its world congress. O'Day (1982) provided an overview of the cause of water-main breaks and leaks. The IWA published a manual of the best practice containing sets of water supply services indicators (Alegre *et al*., 2000; 2006). The Louisville Water Company provided one example of this model, including a detailed scoring system that assigns points based upon 23 factors (Bates and Gregory, 1994). No standard weighting system for water pipes has been developed for the water supply system all over the world. Usually, the factor weights are determined empirically by experts (Yan and Vairavamoorthy, 2003) or based on statistical models (Al-Barqawi and Zayed, 2006a; Geem *et al*., 2007).

In this study, we proposed a useful model to calculate pipe factor weights using Bayesian inference, successfully incorporating both pervious study and statistical estimation. The factor weights were obtained by fitting the model against water pipe condition. Numerical experiments of different factor combinations were conducted to understand the influence of each factor on model performance. Then, we obtained a simplified model containing fewer factors. The new simplified model needs less factor information, and balances the performance and complexity. This Bayesian method incorporated empirical estimation and practical decisions, reducing investigation cost, and improving the accuracy of assessment.

2 Water pipe assessment

The proposed definition of pipe condition assessment is to evaluate the readiness of a component to perform its function (Grigg, 2005). Traditionally, condition assessment was linked to maintenance practice and record information from management (Hudson *et al*., 1997; Grigg, 2006). Makar and Kleiner (2000) reported that there are two main methods to assess the condition of a water system.

In the first method data is collected on pipe conditions (e.g., pipe material and age) and statistical models are developed to assess the condition of the water system elements. The pipe condition data can be categorized into physical, environmental, and operational factors (Reckhow, 1994; Federation of Canadian Municipalities and National Research Council, 2003). Physical factors include pipe age, diameter, pipe material, pipe vintage, wall thickness, dissimilar metals, type of joints, pipe lining and coating, manufacture processes, and thrust restraint. Environmental factors include groundwater presence, soil type, soil moisture, climate, pipe bedding, pipe location in the road, trench backfill materials, stray electrical currents, installation practices, seismic activity, and underground disturbances. Operational factors include water quality, internal water pressure, backflow potential, leakage, flow velocity, operational, and maintenance practices.

In the second method, direct inspection is used to identify problems with underground infrastructure by applying destructive or nondestructive evaluation techniques (NDTs). The popular methods for direct inspection include acoustics, sounding, coupon sampling, the remote field eddy current (RFEC) technique, and the controlled destructive evaluation (CDE). NDTs can avoid catastrophic failure and protect structural integrity; and thus, NDTs are more popular than destructive technologies when they work effectively (Grigg, 2006). Today, many of the evolving methods for pipe assessment rely on NDTs or nondestructive testing (Grigg, 2004).

Both the statistical and inspection methods have advantages and disadvantages. Statistical methods are more efficient, but provide less exact information on pipe conditions. Inspection methods provide more information, but are also more expensive. Thus, statistical models can be used first to identify if the pipe is in a potentially critical situation, then NDTs can be applied to determine the exact condition. Over the past two decades, several statistical methods have been used to assess pipe conditions, such as artificial neural networks (ANNs) (Al-Barqawi and Zayed, 2006a), analytical hierarchy process (AHP) (Al-Barqawi and Zayed, 2006b) and fuzzy rule-based modeling (Yan and Vairavamoorthy, 2003). From these studies, the factor weights for pipe assessment are shown in Table 1.

Table 1 Factors and relative weights of pipe assessment

Factor	Weight	Factor	Weight
Diameter	0.13	Outer coating	0.05
Pressure head	0.06	Electric recharge	0.04
Pipe age	0.26	Bedding condition	0.04
Trench depth	0.04	Soil condition	0.08
Number of road lanes	0.04	Pipe material	0.18
Inner coating	0.08		

3 Bayesian inference

Bayesian statistics provide rigorous methods for uncertainty analysis and key information for parameter fitting (Reckhow, 1994; Ellison, 2004). All unknown parameters, θ, are treated as random variables and their distributions are derived from the previous information (priors) and newly available data (contained in a likelihood function):

$$p(\theta \mid y)=\frac{p(\theta)p(y \mid \theta)}{p(y)}=\frac{p(\theta)p(y \mid \theta)}{\int_\theta p(\theta)p(y \mid \theta)\mathrm{d}\theta}, \quad (1)$$

where $p(\theta|y)$ is the posterior probability of θ, the conditional distribution of the parameters after analysis of the data, θ is the parameter needing estimation, $p(\theta)$ is the prior probability of θ, and $p(y|\theta)$ is the likelihood function representing the probability for the occurrence of the conditions y given different realizations of the postulated mechanistic relationship between the response and predictor variables.

In the Bayesian theory, the prior probability distribution is usually based on previous studies. Then, the prior probability distribution and the likelihood are used to generate the posterior probability distribution. The posterior probability distribution is an epistemological alternative to P-values and offers a direct degree measure of the belief put on hypotheses, parameter estimates, or models (Ellison, 2004). Bayesian inference is a popular statistical method used in many different research fields. Engineers have also begun to use Bayesian inference to understanding pipe condition, e.g., Watson *et al*. (2004) applied a Bayesian approach to incorporate previous practical experience into an incomplete breakage dataset, and thus, obtaining a decision support system.

In this study, we used the Markov Chain Monte Carlo (MCMC) method for solving the Bayesian posterior distribution numerically. The Bayesian idea underlying the MCMC implementation is to construct a Markov process on the condition of stationary distribution, and then produce an accurate distribution approximation by running the process long enough (Malve and Qian, 2006). There is no distinction in using Bayesian theorem between estimation parameters and model inputs, such as external input, missing values of state variables, or unobserved initial conditions. Any unknown quantity can be estimated if the combination of the prior distribution and likelihood function provide sufficient information (Stow and Scavia, 2009).

4 Data source

Water pipe data used in this study were provided by Geem *et al*. (2007). Geem *et al*. (2007) applied an ANN model to calculate deterioration rates of water pipes by analyzing five pipe factors: outer corrosion, crack, pin hole, inner corrosion, and H-W C value (Table 2). The deterioration rates range from 0 to 1: a value of zero indicating that the pipe is in critical condition and requires immediate repair or replacement; a value of one indicating that the pipe is in excellent condition and requires no action. We employed 19 records of pipe condition as shown in Geem *et al*. (2007). Geem *et al*. (2007) assessed three types of pipes, including cast iron, ductile cast iron and steel; while in this study we combined these three types of pipes together to make pipe material as one factor for pipe assessment. Thus, we consider 11 pipe factors for condition assessment, as shown in Table 3.

5 Method

The model equation used to calculate pipe deterioration rates is given as Eq. (2) (Geem *et al*., 2007), and is the usual expression to calculate pipe deterioration rates in pipe condition assessment (Rogers and Grigg, 2009):

$$G=\sum_{i=1}^{I}\lambda_i \cdot x_i, \quad (2)$$

Table 2 Factors for calculating deterioration rates (Geem *et al.*, 2007)

Factor	Description
Outer corrosion	1=corrupted, 0=otherwise
Crack	1=cracked, 0=otherwise
Pin hole	1=punched, 0=otherwise
Inner corrosion	1=corrupted, 0=otherwise
H-W C value	Divided by 150 (range=55–150)

Table 3 Description of Bayesian model factors (Geem *et al.*, 2007)

Factor	Description
Diameter	Divided by 1500 (range=250–1500 mm)
Pressure head	Divided by 12 kg/cm^2 (range=0.5–12 kg/cm^2)
Pipe age	Divided by 28 years (range=5–28 years)
Trench depth	Divided by 5.5 m (range=1–5.5 m)
Number of road lanes	–
Inner coating	Not coated=0; coated=1
Outer coating	Not coated=0; coated=1
Electric recharge	Not recharged=0; charged=1
Bedding condition	Non foundation work=0; foundation work=1
Soil condition	Clay-type=0; sand-type=1
Pipe material	Cast iron=0.8; ductile cast iron=0.8; steel pipe=0.9

where G is the deteriorated rates of pipe, i is the pipe factor, I is the total number of pipe factors, λ is the weight of pipe factor, and x is the factor situation.

We added an error term ε to incorporate Eq. (2) into the Bayesian theorem, and the assumed ε is normally distributed with zero mean and the variance of σ^2, $\varepsilon\sim N(0, \sigma^2)$. This error term represents the uncertainty of pipe situation.

$$G = \sum_{i=1}^{I} \lambda_i \cdot x_i + \varepsilon. \tag{3}$$

The likelihood function of Eq. (3) is

$$\prod_{h=1}^{H} \frac{1}{\sqrt{2\pi\sigma^2}} \exp \frac{\left(G - \sum_{i=1}^{I} \lambda_i \cdot x_i \right)}{-2\sigma^2}. \tag{4}$$

Studies were analyzed in three stages. Firstly, we used the pipe data (pipe deterioration rates and factor situations) to generate relative factor weights. We started with values recommended by experts, and generated the best values of factor weight using Bayesian inference. We used WinBUGS (version 1.4.3) for all MCMC Bayesian fitting. In WinBUGS, the informative normal priors used was $\lambda\sim N(,)I(0,)$, where the numbers in the left set of brackets represent the means and the standard deviation of the corresponding normal distributions, and '$I(0,)$' denotes the censoring imposed to give a bound of factor weight values during the Bayesian updating process. In the second stage, we evaluated the relative influence of each factor on model performance. For these tests, one factor was estimated at a time, the other factors with assigned values from previous study (Table 1). By analyzing the uncertainty bands of marginal posterior distribution of factors, we could determine how each factor contributed to pipe condition. Finally, we tried to obtain a simplified model containing fewer factors while keeping the predictions at a realistic level. From the first stage, we identified factors with small weight. From the second stage, we found factors to which model performance was less sensitive, and then we carried out seven numerical experiments to check if the model could accurately fit pipe condition observations without the identified factors.

We used two chains to carry out the sampling, each with 20 000 iterations. After model convergence, the first 10 000 iterations were discarded. The next 10 000 iterations samples were taken for each unknown quantity, and we used a thin equal to 40 to reduce serial correlation. Rhat is the potential scale reduction factor to show the model convergence, and is produced in package R2WinBUGS. Rhat is approximately the square root of the variance of the mixture of all the chains divided by the average within-chain variance; if it is equal to 1.0, the chains have mixed well (Gelman and Hill, 2007).

Three measures of fit were used to test and compare model results.

1. Deviance information criterion (DIC)

DIC is a measure of model fit and complexity. A larger DIC value indicates a poorer fit between the original data and predicted values. DIC have already been used for comparing models in a variety research fields (Spiegelhalte *et al.*, 2002).

For a Bayesian model with data y, unknown parameters θ, and the likelihood function $p(y|\theta)$, the deviance is defined as

$$D(\theta) = -2\lg[p(y \mid \theta)] + c, \tag{5}$$

where c is a constant. The effective number of parameters in the model is

$$pD = \overline{D(\theta)} - D(\bar{\theta}), \tag{6}$$

where $\bar{\theta}$ is the expectation of θ. $\overline{D(\theta)}$ is the expectation of $D(\theta)$:

$$\overline{D(\theta)} = E^{\theta}[D(\theta)], \tag{7}$$

and DIC is defined as a classical estimate of fit, plus twice the effective number of parameters:

$$\mathrm{DIC} = pD + \overline{D(\theta)}. \tag{8}$$

2. The coefficient of determination R^2

R^2 is defined as

$$R^2 = 1 - \frac{SS_\mathrm{E}}{SS_\mathrm{T}} = 1 - \frac{\sum_{i=1}^{n}(y_i - y_i')^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}, \tag{9}$$

where SS_E and SS_T are the sum of squared errors and total sum of squares, respectively; y_i and y_i' are the original data and predicted mean values, respectively; $\bar{y}_i$ is the mean of the observations y_i; and n is the number of observations. R^2 provides a measure of how well future outcomes are likely to be predicted by the model. But it is essentially a non-Bayesian assessment of the model performance, because the Bayesian inference generates a predictive distribution and not a single value for the variables.

3. Standard error

The standard error is the standard deviation of the sampling distribution associated with the estimation method (Exeritt, 2003), represents genuine uncertainty, and cannot be reduced by obtaining additional real data.

6 Results

As described in Eq. (2), λ_i are the factor weights to be estimated. G represents measured input-deterioration rates of the pipes, and was assumed to be known without error. We fit the model to G with the information on pipe factors, and the resulting factor weights are in Table 3. Most calculated pipe deterioration rates were included within the 2.5% and 97.5% credible intervals (Fig. 1). The posterior estimates of some factor weights (Table 4) were comparable to those in Table 1, including diameter, pipe age, and soil condition; however, some were quite a bit different from the prior probabilities, such as pressure head, inner coating, and pipe material. In this study, the pressure head, inner coating and pipe material contributions to pipe assessment were 11%, 7%, and 11%, respectively; however, in Al-Barqawi and Zayed (2006b)'s analytic hierarchy process (AHP) model, they are 6%, 4%, and 17%, respectively. The results also showed that weights for the factors described as the number of road lanes, trench depth and electric recharge were small (no more than 5%), indicating that these three factors had less influence on pipe condition.

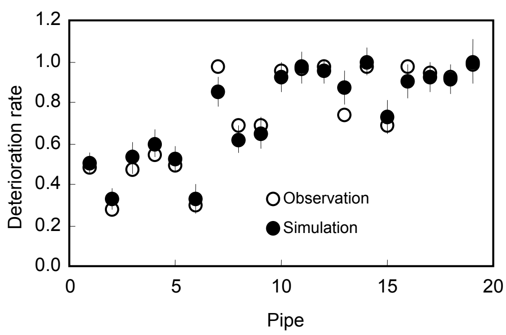

Fig. 1 Deterioration rates of observation and Bayesian model

Table 4 Factor weights of the Bayesian model

Factor	Weight			R^2	DIC
	Mean	2.5%	97.5%		
Diameter	0.12	0.020	0.320		
Pressure head	0.11	0.010	0.290		
Pipe age	0.21	0.090	0.380		
Trench depth	0.05	0.009	0.270		
Number of road lanes	0.05	0.005	0.230		
Inner coating	0.07	0.007	0.250	0.75	−3.82
Outer coating	0.09	0.004	0.200		
Electric recharge	0.04	0.006	0.087		
Bedding condition	0.07	0.020	0.250		
Soil condition	0.08	0.011	0.220		
Pipe material	0.11	0.030	0.330		

Factors were then estimated individually to evaluate the influence on model performance. For these tests, one factor was estimated and the other ten factors were assigned values from previous study (Table 1). Table 5 shows the estimation results. The marginal posteriors of trench depth, bedding condition, and electric recharge were associated with narrower prediction uncertainty bands; and thus, the model performance was less sensitive to variations of these three factors, which meant the pipe deterioration rates data contains less information about these three factors.

Table 5 Goodness-of-fit for the factors

Estimated factor	R^2	Model standard error		
		Mean	2.5%	97.5%
Diameter	0.55	0.24	0.18	0.36
Pressure head	0.50	0.21	0.18	0.36
Pipe age	0.57	0.26	0.19	0.38
Trench depth	0.43	0.17	0.13	0.26
Number of road lanes	0.51	0.22	0.19	0.37
Inner coating	0.53	0.23	0.17	0.34
Outer coating	0.50	0.25	0.19	0.36
Electric recharge	0.43	0.20	0.16	0.35
Bedding condition	0.42	0.21	0.177	0.344
Soil condition	0.50	0.25	0.19	0.36
Pipe material	0.53	0.23	0.16	0.35

The marginal posterior distribution of pipe age was associated with broader prediction uncertainty bands (Fig. 2). The finding can be interpreted as evidence that pipe deterioration rates are more sensitive to the prior distribution specifications of pipe age, and formulating more articulate priors for this factor can significantly control the predictive uncertainty. Even a prior distribution with a small variation of the factor pipe age may have only a modest influence on the posterior distribution. This result is consistent with pervious studies: pipe age is the most important factors for pipes condition. Many aging models have been used to evaluate the probability of pipe deterioration (Kettler and Goulter, 1985).

Other factors, such as inner coating and outer coating, are important for pipe condition. Inner corrosion in aging cast iron pipes can lead to mechanical failure in terms of water leakage and loss of hydraulic capacity due to buildup of corrosion products (Yamini and Lence, 2006). External corrosion has been shown to significantly affect the likelihood of mechanical failure; the risk of failure may be further heightened if inner corrosion is occurring (Dodrill and Edwards, 1995). From the pipe data in this study, the mean standard errors of inner and outer coatings are 0.23 and 0.25, respectively. The assessment results of pipes are sensitive to inner and outer coatings. Pipe diameter is also considered to be a significant factor for water pipe assessment. Previous study showed strong inverse correlation between failures and diameter (0.0625 fewer annual failures/km of main with each centimeter of larger pipe diameter, for diameters between 100 and 300 mm) (Kettler and Goulter, 1985). The mean standard error was 0.24 in our study, and it confirmed the importance of the pipe diameter in statistical pipe assessment.

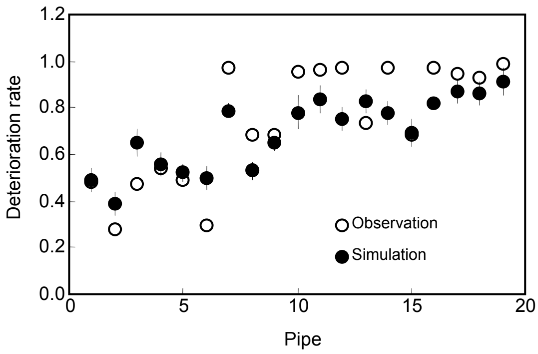

Fig. 2 Estimation of factor "pipe age"

From the above results, the factors number of road lanes, trench depth, and electric recharge had small weights and model performance was less sensitive to their variation. Thus, we conducted numerical experiments of different factor combinations to identify if one or more of these factors could be excluded from the assessment model without loss of prediction ability. Seven different experiments were completed, including all combinations of the three factors.

For the seven experiments, we found no significant differences among model measures of fit—R^2, DIC, and model error values (Table 6), which means all the seven models provide similarly good fits. From the results of measures, we came to the conclusion that water pipe condition can be assessed without the information on road lane, trench depth, or electric recharge. Thus, we developed a simplified model that balanced performance and complexity (Fig. 3). Factors and weights are shown in Table 7.

Table 6 Joint factor estimations

Model	R^2	DIC	Model standard error		
			Mean	2.5%	97.5%
Previous model	0.75	−3.82	0.20	0.14	0.29
Without number of road lanes	0.68	1.29	0.23	0.16	0.33
Without trench depth	0.71	−2.81	0.21	0.15	0.30
Without electric recharge	0.72	−4.23	0.20	0.14	0.29
Without number of road lanes and trench depth	0.68	2.71	0.24	0.17	0.34
Without number of road lanes and electric recharge	0.69	1.16	0.23	0.17	0.33
Without trench depth and electric recharge	0.71	−3.17	0.21	0.14	0.30
Without number of road lanes, trench depth, and electric recharge	0.67	2.89	0.24	0.17	0.34

Table 7 Factors and weights of the simplified model

Factor	Weight			R^2	DIC
	Mean	2.5%	97.5%		
Diameter	0.21	0.05	0.39	0.67	2.75
Pressure head	0.19	0.03	0.36		
Pipe age	0.34	0.20	0.34		
Inner coating	0.15	0.02	0.26		
Outer coating	0.12	0.01	0.27		
Bedding condition	0.17	0.04	0.30		
Soil condition	0.12	0.015	0.26		
Pipe material	0.27	0.06	0.38		

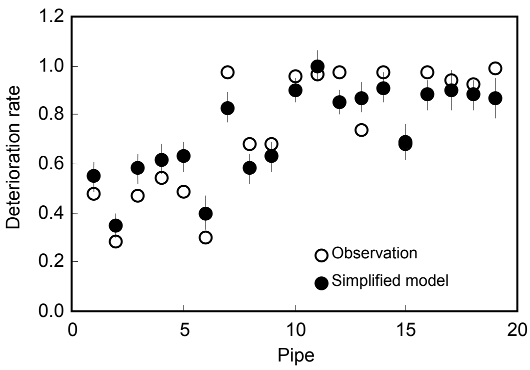

Fig. 3 Deterioration rates of observation and simplified Bayesian model

Model sensitivity to factor weight priors was done by doubling and dividing the original prior in half. We discuss one of these cases here in detail: estimated factor weight of the simplified model. When doubling the precision of the parameter priors (cutting the variance in half), overall model performance became relatively bad, as indicated by R^2 and wider credible intervals of the predicted deteriorated rates (Fig. 4). When the precisions were reduced, the prior factor weight space was expanded, which in principle increases the odds of locating the global optima of the model (Fig. 5). The fact that there was no significant improvement of model performance increases our confidence that the original specification of the informative priors did permit sufficient coverage of the model likelihood and that the posterior inferences drawn herein were not biased from the selection of the factor weight priors.

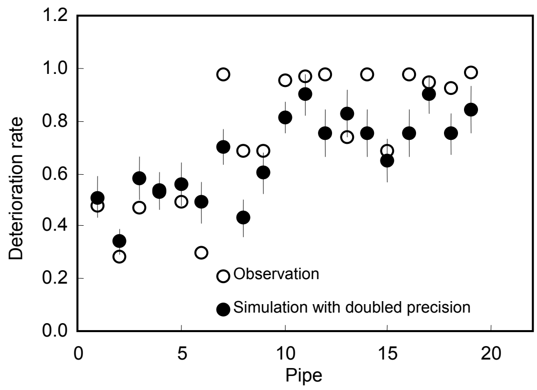

Fig. 4 Deteriorated rates of Bayesian model with doubled precision

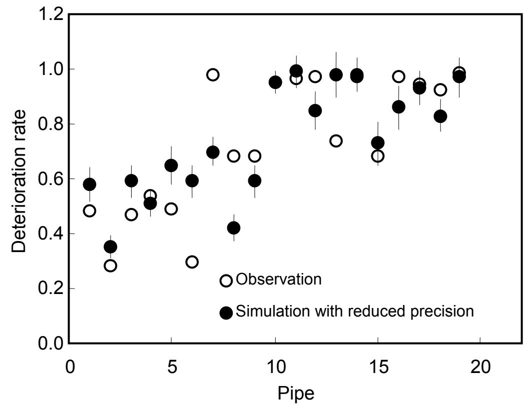

Fig. 5 Deteriorated rates of Bayesian model with reduced precision

7 Discussion

The present analysis used a Bayesian framework for pipe deterioration rates modeling, factor weight estimation and factor selection. This Bayesian framework provides advantages over modeling in three ways: (1) Inference was an effective method to obtain pipe condition; (2) Model analysis shows the influence of each factor on pipe condition. When utilities face obstacles such as shortage of information or funding, one can point out which factors are necessarily needed and which factors could be ignored, and thus, further reducing the assessment expense; (3) This analysis also indicates that model predictions of pipe condition are more sensitive to the prior specifications of some factors, and therefore, the predictive uncertainty can be significantly controlled by formulating factor pipe age, soil condition and inner coating. Prior distributions with more realistic central tendencies and dispersion values represent the dynamics of the system. For example, it seems feasible to delineate an articulate prior for the pipe condition by pipe age, and this may be more difficult with other parameters, such as the number of road lanes.

The factors used to assess pipe condition should be tailored for different utilities and assessment goals. These factors will often be similar since most utilities have similar objectives and charges, but there will be differences based on condition, location, and the availability of information to determine necessary factors. The process of pipe deterioration is also complicated. A number of studies have reported on how various factors cause pipes to fail. Male and Walski (1990) discussed various pipe failure modes, while Kirmeyer *et al.* (1994) surveyed utilities to determine modes of pipe failure. Dingus *et al.* (2002) reported failure mechanisms of pipe 16 inches (46 cm) and similar size. In this study, we used the Bayesian approach to understand how the factors contribute to pipe failure statistically. This means we can select factors by analyzing pipe data instead of pipe mechanisms, which is more direct and convenient for pipe assessment.

To be useful, however, statistical models must overcome some basic problems. These problems include the uncertainty associate with unique operating situations errors in measurement, and uneven sampling of pipe conditions. To address this, we incorporated additional information with the original dataset during the model fitting process. Informative priors used for factor weights were based upon the literature and expert opinion. This Bayesian inference combines previous experience and practical situations, and leads to optimized returns on the investments in distribution systems for utilities. Furthermore, information on pipe condition, such as pipe deterioration rates in this study, is needed to apply this Bayesian inference. Experts have recommended several methods to identify pipe condition, including remaining wall thickness (Al-Barqawi and Zayed, 2006b), summarization of pipe factors condition (Geem *et al*., 2007), and ratio of residual strength and stress by internal and external loads (Kim *et al.*, 2007). There is, however, currently no standard system for water pipes condition. Factor weights may be different for different assessment systems of pipe condition. Furthermore, application of this Bayesian approach also needs to overcome the deficiency in pipe factor data. Utilities face obstacles, such as lack of records, and of motivation to invest in pipe condition assessment. To maximize the benefits of Bayesian information consolidation, utilities should collect available and inventory information of pipe operation, manage existing data, and use statistical methods to organize data effectively. Then, the existing information can be used by committing to implementation of an organized condition assessment program. American Water Works Association Research Foundation (AWWARF) has funded a number of studies related to distribution systems and continues to maintain an inventory of research needs. Statistical models, such as the Bayesian approach, predict efficient and synthetic pipe condition only together with qualified pipe factor data.

The limit in pipe condition assessment is not technological but economic (Grigg, 2004). We need to find economical ways to assess pipe condition rapidly and reliably. Much potential is hidden in the use of existing data and experiences of operational employees. Research on how to learn from limited data shows potential, but even more potential exists from using readily available information to make better decisions. The Bayesian inference method makes good use of these potentials and helps researchers to make better decisions.

8 Conclusions

This work demonstrates the feasibility of applying Bayesian theory in water pipe assessment. The method provides a mathematical framework for obtaining factor weights with distributions of water pipes. Most of the obtained factor weights are comparable with the previous study, though factor weights of pressure head, inner coating and pipe material are somewhat different. The Bayesian method combines both engineering knowledge and the practical situation of the pipes. Informative priors are used to alleviate the identification problems when switching from assessing pipe condition to real pipes. Factors were estimated individually to evaluate the influence on model performance using the Bayesian method. The results were consistent with previous mechanistic studies: pipe age is the most significant factor in judging pipe condition; while inner coating, outer coating and diameter were also important. Numerical experiments are particularly useful for optimizing expert model complexity by eliminating redundant factors. The examples of steel, cast iron and ductile cast iron pipe in this study showed that water pipe condition can be assessed without information on road lane, trench depth, or electric recharge. This Bayesian inference combines estimation and statistical analysis to produce a model framework that could reduce pipe assessment cost and improve the accuracy of water system assessment.

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