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# Evaluating risk of water mains failure using a Bayesian belief network model

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ABSTRACT

It has been reported that since year 2000, there have been an average 700 water main breaks per day only in Canada and the USA costing more than CAD 10 billions/year. Moreover, water main leaks affect other neighboring infrastructure that may lead to catastrophic failures. For this, municipality authorities or stakeholders are more concerned about preventive actions rather reacting to failure events. This paper presents a Bayesian Belief Network (BBN) model to evaluate the risk of failure of metallic water mains using structural integrity, hydraulic capacity, water quality, and consequence factors. BBN is a probabilistic graphical model that represents a set of variables and their probabilistic relationships, which also captures historical information about these dependencies. The proposed model is capable of ranking water mains within distribution network that can identify vulnerable and sensitive pipes to justify proper decision action for maintenance/rehabilitation/replacement (M/R/R). To demonstrate the application of proposed model, water distribution network of City of Kelowna has been studied. Result indicates that almost 9% of the total 259 metallic pipes are at high risk in both summer and winter.



## 1. Introduction

Water distribution networks (WDNs) are among the most important and expensive municipal infrastructure assets (Berardi, Giustolisi, Kapelan, & Savic, 2008), and vital to public health. Potable water and wastewater conveyance system are spatially distributed assets and 1.6 million miles of pipelines lay beneath North America's roads (Agarwal, 2010). American Society of Civil Engineers (ASCE) (2013) Report Card for America's Infrastructure gave a grade of "D" to water/wastewater infrastructure. Canada's first national infrastructure Report Card (2012) indicated that a significant amount of drinking-water, stormwater and wastewater infrastructure are in "fair" to "very poor" condition. The replacement costs of these assets are $25.9, $15.8 and $39 billions, respectively. According to the Infrastructure Report (2007), there have been more than 2 million breaks in Canada and the United States since January 2000, with an average of 700 water main breaks every day, costing more than CAD 10 billions/year. Moreover, water main leaks affect other existing nearby infrastructures such as sewer, storm water, pavement, and gas pipes that may lead to catastrophic failures (US EPA, 2011). The water main failure risk mitigation has transformed reactive to preventive actions of water main maintenance. Thus, risk-based decision making is taking prominence (e.g., Anwar, Koester, & Harlow, 2005; Bennett, Bohoris, Aspinwall, & Hall, 1996; He & Huang, 2008; Kleiner, Rajani, & Sadiq, 2005; Marlow, Beale, & Mashford, 2012; Matos, 2007; Sadiq & Rodriguez, 2004; Sorge, Christen, & Malzer, 2013; Tesfamariam, Sadiq, & Najjaran, 2010; US EPA, 1995).

Failure risk is combination of probability and impact severity of a particular situation that negatively affects the ability of infrastructures to obtain municipal objectives (InfraGuide, 2006), which is in congruence with Lawrence's (1976) risk definition. A successful risk assessment program provides predictive tools to evaluate water mains failure, assess the consequences associated with such failures, and recommend prioritization strategies for capital and operating spending (Moustafa, 2010). As well, this tool enables municipalities and other authorities to build long- and short-term management plans. It is important to determine the cause and effect of probability of failure, where failure can manifests as structural integrity, hydraulic capacity and water quality (Al-Barqawi & Zayed, 2008; Christodoulou, Deligianni, Aslani, & Agathokleous, 2009; Fares & Zayed, 2010; Sadiq, Kleiner, & Rajani, 2010) and consequences (e.g. Fares & Zayed, 2010; Francisque, Rodriguez, Sadiq, Miranda, & Proulx, 2009). These strategies should be built on scientific approaches that combine human knowledge and experience as well as expert judgment to consider the risk of water main failure.

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Despite some differences, the performance objectives for risk of failure of water mains can broadly be categorized as: water quality index (WQI), hydraulic capacity index (HCI), structural integrity index (SII) and consequences index (CI) (Al-Barqawi & Zayed, 2008; Infrastructure Report, 2007). Christodoulou et al. (2009) included eight significant factors like number of observed previous breaks, diameter, length, material, traffic load, proximity to highway, proximity to subway, and proximity to roadway/block intersection in the study. Al-Barqawi and Zayed (2008) classified factors contributing to water main deterioration into physical, environmental and operational factors. Fares and Zayed (2010) categorized the model structure into four main factors and sixteen factors which represents the deterioration and post-failure factors. A summary of contributing risk factors of water main failure reported in different studies is presented in Table 1.

Different water main failure models have been reported to quantify risk factors of water main failure and infrastructure deterioration. When significant historical data exist, model-free methods, such as Artificial Neural Networks (ANN), can provide insights into cause-effect relationships and uncertainties through learning from data (e.g. Christodoulou, Aslani, & Vanrenterghem, 2003; Ismail, Sadiq, Soleymani, & Tesfamariam, 2011 and Najafi & Kulandaivel, 2005). But, if historical data are scarce and/or available information is ambiguous and imprecise, other soft computing techniques can provide appropriate framework to handle such relationships and uncertainties (e.g., Bolar, Sadiq, & Tesfamariam, 2013; Cockburn & Tesfamariam, 2012; Deng, Sadiq, Jiang, & Tesfamariam, 2011; Flintsch & Chen, 2004; Ismail et al., 2011; Janssens et al., 2006; Lauría & Duchessi, 2007; Najjaran, Sadiq, & Rajani, 2005; Poropudas & Virtanen, 2011; Sadiq & Rodriguez, 2004; Sun & Shenoy, 2007; Tesfamariam & Najjaran, 2007). Table 2 provides a qualitative comparison between six networks based computing techniques including ANN, Analytic Network Process (ANP), Bayesian Belief Network (BBN), Cognitive Maps/Fuzzy Cognitive Maps (CM/FCM), Credal Network (CN) and Fuzzy Rule-Based Models (FRBM). Central to this comparison is an assessment of how each technique treats inherent uncertainties and its ability to handle interacting factors that encompass issues specific to failure of water mains.

The ANN has been used by Christodoulou et al. (2003) and Najafi and Kulandaivel (2005) to analyze the failure risk of water main and sewer in an urban area with historical breakage data, respectively. Christodoulou et al. (2003) indicated that the number of previous breakage, diameter, material, and length of pipe segments were the most important factors for water main failure. Modeling of breaks in the water networks was carried out using multiple regression and ANN by Jafar et al. (2003). Al-Barqawi and Zayed (2006a, 2008)developed rehabilitation priority for water mains using ANN approach. Their results showed that the breakage rate has the highest relative contribution factor followed by age. Amaitik and Amaitik (2008) developed pre-stressed concrete cylinder pipe wire breaks prediction model using ANN. Failure rate and the optimal replacement time for the individual pipes of urban water distribution system were estimated using ANN by Jafar, Shahrour, and Juran (2010).

Kleiner, Sadiq, and Rajani (2004) used a fuzzy rule-based non-homogeneous Markov process to model the deterioration procedure of buried pipelines. The deterioration rate at a specific time is estimated based on the asset's age and condition state using a fuzzy rule-based algorithm. Fuzzy sets and fuzzy-based techniques were proposed to evaluate pipeline failure risk by Kleiner, Rajani, and Sadiq (2006). For prioritizing monitoring locations (zones) in a WDN, Francisque et al. (2009) coupled the concept of risk with fuzzy synthetic evaluation and fuzzy rule-base. To evaluate the risk of water main failure considering both consequence and deterioration factors and to develop a risk scale of failure, Fares and Zayed (2010) used hierarchical fuzzy expert system framework. Christodoulou et al. (2009) proposed neurofuzzy systems to assess the risk of failure in a network. Tesfamariam, Rajani, and Sadiq (2006) have proposed a possibilistic based pipe failure risk using Rajani and Tesfamariam (2004) mechanistic models. Rajani and Tesfamariam (2007) have extended these models with fuzzy deterioration model to estimate remaining service lives.

Joseph, Adams, and McCabe (2010) proposed BBN to support the water quality compliance of small or rural water distribution systems. Expert judgment was used to quantify the required probability relationships. However, it is usually difficult to establish mutual relationships among nodes in the network solely based on the knowledge of experts, particularly for complex problems (Nadkarni & Shenoy, 2001). If a node in a BBN has several parent nodes or each parent node and child node has several states, the number of conditional probabilities will be increases exponentially (Tang & McCabe, 2007). For example, if a child node has three parent nodes and the number of their states is five, the total number of conditional probability table (CPT) values can be a great as $5^4$ (625) (Lauría & Duchessi, 2007). The elicited conditional probabilities defined by experts can be inconsistent, especially under the complex and large CPT condition. Joseph et al. (2010) limited the maximum number of parent nodes for any variable into three. However it is not possible to always represent the causal effect properly with only three variables. In that situation, it is more reliable and consistent to construct CPTs training from data (Cooper & Herskovits, 1992; Hager & Andersen, 2010; Tang & McCabe, 2007). To find out the posterior probabilities of water main failure starting from the prior probabilities of failure based on the age at failure, pipe diameter, cause of break and type of soil for specific type of pipe using Bayes' theorem proposed by Singh (2011). But the author assumed these contributing risk factors independent and the causal dependencies among the variables have not been taken into consideration. Furthermore the author did not mention what will be the failure probabilities if all these risk factors affects simultaneously and how to update posterior probabilities when new failure information available.

Objective of this research is to develop a new and effective model to evaluate the risk of water main failure considering structural integrity, hydraulic capacity, water quality, and consequence factors. This paper explores both knowledge and data based BBN model to evaluate water main failure risk index that can be used to rank or prioritize the water main in a network system for M/R/R. In this research, deterioration factors that lead to the failure event and the consequence factors that result from the failure event (failure impact) are studied. Such decision support systems will aid the utility manager to better address the structural and hydraulic failure of water mains, proactively, while meeting financial constraints, level of service, and regulatory requirements.

## 2. Bayesian Belief Network (BBN)

### 2.1. Background

Bayesian belief network is a graphical model that permits a probabilistic relationship among a set of variables (Pearl, 1988). A BBN is a Directed Acyclic Graph, where the nodes represent variables of interest and the links between them indicate informational or causal dependencies among the variables (Cockburn & Tesfamariam, 2012; Hager & Andersen, 2010; Laskey, 1995). As depicted in Fig. 1, a BBN is composed of:

(a) a set of variables (e.g. $A_1$, $A_2$ and $B$) and a set of directed links between the variables;