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Consequence-based framework for buried infrastructure systems: A Bayesian belief network model

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ABSTRACT

The failure of municipal buried infrastructures (potable water supply, wastewater systems, and stormwater systems) may cause crucial consequences to the environment, society, health, and economy. The buried infrastructure management has transformed from reactive to the preventive action plan. In this study, a Bayesian belief network (BBN) based buried infrastructure consequence model is developed to assess the consequence index and to prioritize the buried infrastructures for maintenance/ rehabilitation/ replacement. The causal relationships between different parameters are constructed based on published literature and expert knowledge. The proposed model can provide information at pipe level by estimating the health & safety impact, environmental impact, social impact, and economical & organizational impact due to failure. The proposed model is also capable of highlighting the most sensitive and vulnerable pipes within the network. The applicability of the proposed model is demonstrated on the wastewater collection network of the City of Vernon, BC. Results indicate that proposed BBN-based consequence model can explicitly quantify uncertainties and handle the nonlinear and sophisticated relationships between several factors.

1. Introduction

Failure of buried infrastructures can impact health, social and economic factors that can also affect public confidence [27]. The risk-based maintenance/ rehabilitation/ replacement (M/R/R) framework has been used for the prioritization of buried infrastructures (potable water supply, wastewater systems, and stormwater systems) by considering the likelihood and consequences associated failures [3,21]. A better knowledge of buried infrastructure condition and the magnitude of their potential consequences on consumers, business, and socio-economic activities in case of the event of failure may urge utility managers to implement preventive measures [1,37].

However, this is difficult for small and medium sized utilities as they often suffer from data/information scarcity and lack of technical, financial and expert resources [2,16,23]. Therefore, for the likelihood of failure assessment, they should rely on the models of large utilities which are highly uncertain for decision making as buried infrastructure failure models are site and location specific [1]. Furthermore, it takes a long time to generate their own database for buried infrastructure failure models as few mains fails in a year compared to the large utilities. On the other hand, due to the small distribution systems, less population, land use, and few facilities, it will be more feasible for the small to medium-sized utilities to develop the database with higher credibility and confidence for consequence-based decision making. Therefore, there is a need of an effective consequence-based decision support tool that considers several consequence dimensions during the assessment of M/R/R action plans.

The risk-based decision support framework underestimates low probability high consequence events, such as earthquakes, tsunami, and floods although today's society is consistently exposed on these events [5,40]. For this, consequence-based decision-making framework have been previously proposed for different applications, e.g. building, dam, road network, process unit. Consequence-based engineering approach is first used for buildings in a region of low-to-moderate seismicity [41]. Tugnoli et al. [39] developed a consequence-based approach for the quantitative assessment of inherent safety of the process units. Buriticá and Tesfamariam [5] proposed a Consequence-based framework for electric power providers considering six performance objectives (i.e., health and safety, reputation, reliability, financial, environmental, and system conditions). Cleary et al. [9] presented a scenario-based risk framework to determine the consequences of different failure modes of earth dams. Recently, Moreu et al. [28] proposed a consequence-based management of bridge networks for making network M/R/R decisions. However, the authors considered only the M/R/R decisions costs and

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operational costs for a given M/R/R policy and to improve M/R/R budget decisions within the network. Vairo et al. [40] employed consequence-based approach to assess the cruise ship risk identifying the possibilities of both routine and accidental emissions and accounting the adverse effects. However, no studies proposed any consequence-based framework for buried infrastructure systems.

Therefore, the objective of this paper is to develop a novel and innovative Bayesian belief network (BBN)-based buried infrastructure consequence model. Recently, BBN is presented by different researchers to deal with risk-related issues on water supply and sewer infrastructures. Francis et al. [13] used a knowledge-based BBN model for predicting drinking water distribution system pipe breaks. Kabir et al. [20] presented BBN- based data fusion model for the failure prediction of water mains. In another study, Kabir et al. [21] utilized a knowledge and data-based BBN model for evaluating the risk of water mains failure using structural integrity, hydraulic capacity, water quality, and consequence factors. However, they only used pipe diameter, land use, and population density to estimate the water mains failure consequences. Recently, Elmasry et al. [12] used BBN to develop deterioration model for sewer pipelines using probabilities of occurrences, and conditional probabilities from observations. Anbari et al. [3] proposed a risk assessment model to prioritize sewer pipes inspection using Bayesian networks. However, most of the studies underestimated the consequence of the water mains or sewer failure and gave more concentration on the likelihood of the failure.

To develop an effective risk-based model and to prioritize the buried infrastructures for M/R/R action plan, it is essential to determine the consequences or impacts of infrastructure failure. For this, this study explores knowledge-based BBN model to assess the consequence index of the buried infrastructures that can be used to prioritize the buried infrastructures for M/R/R. In the absence of proper buried infrastructure deterioration model, identifying, evaluating, and prioritizing buried infrastructure based on the consequence of failure can help in estimating and mitigating the risk of buried infrastructure systems. Moreover, the proposed BBN-based model has the capacity to deal with uncertain/missing information if the infrastructure deterioration model is not available. The proposed methodology is discussed for the sewer consequence model development. However, similar analysis can be performed to develop the consequence model for potable water and stormwater mains.

The remainder of this paper is structured as follows. The motivation of the model selection and a brief discussion on BBN is presented in Section 2. The proposed BBN-based consequence model is described step by step in the following section. After that, the proposed model is applied to assess the consequence of the City of Vernon, BC sewer network system. Finally, the conclusions, limitations of the study and scope for further research are discussed.

2. Methodology

2.1. Motivation of model selection

The relationship among the consequence factors is nonlinear and complex interaction required to develop the cause-effect relationships and to determine buried infrastructure consequence index [3,15,21]. To develop an effective consequence-based framework for buried infrastructure systems, the data required from multiple sources such as pipe characteristics data, land use, population data, proximity to the stream, and proximity of other infrastructures like road, pavement. Thus, the data integration can play a vital role in this analysis. As there can be incomplete and partial data, the expert's involvement and judgment might require for data interpretation and elucidation. For this, it is essential to consider the model uncertainties for the consequence assessment of buried infrastructure systems.

Different network-based models like Artificial Neural Networks (ANN), Analytic Network Process (ANP), BBN and Cognitive Maps/Fuzzy Cognitive Maps (CM/FCM) can be used to handle the relationships between the parameters and to consider model uncertainties during analysis. If significant historical data exist, then the ANN-based model can provide insights into cause-effect relationships and uncertainties through learning from data. As the data for consequence analysis are scarce and incomplete especially for the small to medium-sized utilities, other soft computing techniques like ANP, BBN, CM/FCM can provide an appropriate framework to handle such relationships and uncertainties.

The ANP method use pair-wise comparison to represent the causal relationship between the parameters [36]. However, it is difficult to generate the supermatrix even for experts as all the parameters criteria must be pair-wise compared with regard to all other parameter which is also challenging and somewhat unnatural. On the other hand, the CM/FCM allow expressing dependence and feedback among concepts with a degree of an influence (normally from + 1 to −1) of one concept on another [24]. Both ANP and CM/FCM methods cannot represent the cause-effect relationships between the parameters effectively. For example, we have to develop the causal relationship between the water main pressure and hydraulic capacity failure. The water main pressure can represent hydraulic capacity failure through inadequate water supply to the customers, insufficient pressure for firefighting, and possible loss of water due to leakage [33]. It is critical to set the water main operating pressure within a logical range so that the network can continuously provide and maintain adequate hydraulic capacity. Too high pressure may cause failure of water mains resulting from higher complaints, health-related issues, and public security. On another hand, the extremely low pressure will not secure adequate water supply to the customers, can cause contaminant intrusion inside the network during a firefighting event which can cause serious health public problems [14]. The ANP method will indicate the relative importance of water main pressure over hydraulic capacity failure whereas the CM/FCM will represent either positive or negative degree of influence (between + 1 to 0 or 0 to −1) between these parameters. The Bayesian belief network can handle the cause-effect relationships between the water main pressure and hydraulic capacity failure effectively using conditional probability table (CPT).

Table 1 highlights a qualitative comparison between ANN, ANP, BBN, and CM/FCM techniques to highlight how each method handle qualitative and quantitative information and its ability to consider the cause-effect relationships between factors [21]. Based on the

Table 1
Comparison of various network-based techniques (Modified after [21]).

Attributes	ANN	ANP	BBN	CM/ FCM
Ability to express causality	N	L	VH	H
Ability to handle qualitative inputs	N	VH	H	VH
Ability to handle quantitative inputs	VH	L[a]	M[b]	L[c]
Ability to handle dynamic data	H	M	H	M
Ability to model complex systems	VH	M	VH	H
Learning/training capability	VH[d]	H[e]	H[f]	H[g]

Network based techniques: ANN = Artificial Neural Networks; ANP = Analytic Network Process; BBN = Bayesian Belief Networks; CM/FCM = Cognitive Maps/Fuzzy Cognitive Maps
Ratings: N = No or Negligible; VL = very low; L = low; M = medium; H = high; VH = very high

[a] Minimal data requirement, because causal relationships are given by decision makers.
[b] Medium data requirement for using precise probability.
[c] Minimal data requirement, because causal relationships are generally soft in nature.
[d] Training algorithms are available which have been successful in training ANNs.
[e] Algorithms, e.g., minimizing the error function.
[f] Algorithms, e.g., evolutionary algorithms and Markov chain Monte Carlo.
[g] Algorithms, e.g., Hebbian learning.