# A Defect-Based ArcGIS Tool for Prioritizing Inspection of Sewer Pipelines

**By**

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## ABSTRACT

This paper presents a defect based model for assessing risk of failure for sewer pipelines. The proposed model deploys Sugeno fuzzy inference system to create a risk index from which inspection and replacement activities could be prioritized. To determine the likelihood of failure, Dynamic Bayesian Network (DBN) was used as an inference engine to predict sewer pipelines' likelihood of failure based on both the probable defects that could occur and some of the pipelines' characteristics. The consequences of failure was determined using economic loss model that assumes both costs resulting from failure of sewer pipelines and benefits from avoiding such failure. An ArcGIS tool was created using Python programming language to perform Sugeno fuzzy inference method and determine the risk of failure by combining both the likelihood and consequences of failure. To validate the tool, actual data for inspected sewer pipelines in Doha, Qatar was used, in which the pipelines from the model were compared with the inspected pipelines. It was found that the proposed tool could save more than 77% if deployed over the current inspection practices followed by municipalities. It is expected that the resulting risk map would help key personnel in municipalities to identify sewer pipelines that require immediate interventions and would assist in better planning for inspection programs especially in cases of limited funds.

**Keywords:** Risk Assessment, Wastewater Pipelines, Defect Based, ArcGIS, Prioritizing Inspections

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## INTRODUCTION

It is reported that wastewater collection networks in USA have one of the lowest grades (i.e. grade D+) when compared to the rest of infrastructure assets (ASCE infrastructures report card 2017). Additionally, 35% of the wastewater network lengths in Canada are either in fair or very poor conditions (Canadian infrastructure report card 2016). Performing inspections for these deteriorated pipelines could assist decision makers in making informed interventions regarding pipelines' replacement or rehabilitation based on the collected information used in condition assessment. Due to the fact that most municipalities suffer from the presence of limited funds and large number of deteriorated pipelines with a competitive need for inspection, development of prioritization tools is crucially required. These prioritization tools can help in identifying pipelines with the highest risk of failure by integrating two components namely likelihood of failure and consequence of failure.

Several researchers have addressed determining the likelihood of failure for sewer pipelines (Ana 2009; Ariaratnam et al. 2001; Baik et al. 2006; Baur and Herz 2002; Elmasry et al. 2017; Hawari et al. 2016; Kleiner 2001; Kleiner et al. 2005; Le Gat 2008; Ruwanpura et al. 2004; Salman and Salem 2012; Sinha and McKim 2007; Wirahadikusumah et al. 2001). In these researches, pipeline characteristics such as age, diameter, length, function, effluent type, material, surrounding soil and street category were used with the aid of statistical and artificial intelligence techniques to determine the likelihood of a pipeline to be in a certain condition state or whether it would fail or not. One of the main limitations for using pipelines' characteristics in assessing condition of sewer pipelines (i.e. indirect assessment method) is that the accuracy of the results depends on how reliable the data used is. On the other hand using different defects that occur in sewer pipelines to predict the likelihood of failure (i.e. direct assessment method) could provide more reliable and accurate assessment method, however it could be more time consuming and costly. As such, combining both the direct and indirect assessment methods could provide the user with a more reliable and accurate condition assessment method while being time efficient and cost effective. Ennaouri and Fuamba (2011) combined the structural and operational defects with some pipeline characteristics using Analytical Hierarchy Process (AHP) to determine the effect of the different pipeline's characteristics on the deterioration of combined sewer systems. In the same context, Elmasry et al. (2017) used Bayesian Belief Network (BBN) to determine the likelihood of a pipeline to be in a certain condition state based on the probability of occurrence of the different structural and operational defects. Similar research studies were carried out in water distribution networks to assess the condition of the pipelines. Different problems that could affect the operational performance in water distribution networks were studied by Kanakoudis (2004) for water distribution pipelines. In another research, Kanakoudis and Tolikas (2004) presented a methodology for preventive maintenance actions that guaranteed safe failure in water distribution networks. Additionally, reliability prediction model of water pipes was developed by Kanakoudis and Tsitsifli (2011) using discriminant analysis and classification method from which the failure of pipes could be predicted. Performance indicator was also developed for water pipelines using water loss management (Tsitsifli et al. 2011; Kanakoudis et al. 2011; Kanakoudis et al. 2013b). Also, factors affecting performance service contracts in water distribution network projects were identified and studied by Kanakoudis et al. (2013a). In the context of cost benefit analysis, financial and environmental feasibility evaluation of water distribution networks were analyzed

(Kanakoudis 2008). Kanakoudis et al. (2015a); Kanakoudis et al. (2015b) developed a decision support system using decision tree to determine the impact of non-revenue water components on economic, environmental and social aspects in water supply networks. Further to this research, Kanakoudis and Tolikas (2001) developed a methodology for optimum times for replacement of water pipelines by performing an economic analysis after determining the rate of breaks and leakage. Additionally, Kanakoudis (2004) developed a methodology for optimal preventive maintenance schedule by taking into account repair and replacement costs in water distribution networks. Unlike the likelihood of failure, little research studies have addressed the consequences of failure for sewer pipelines in terms of monetary amounts due to the uncertainty accompanying the estimation process (Ana 2009; Martin et al. 2007; Sægrov and Schilling 2002; Salman 2010). In their researches, Ana (2009) and Salman and Salem (2012) used Multi-Criteria Decision Making (MCDM) techniques such as weighted scoring method and Organization Rangement Et Synthese De Donnes Relationnelles (ORESTE) to determine the consequences of failure based on relative importance of certain performance indicators. Although using these techniques could reduce subjectivity and handle uncertainty, they depend heavily on experts' opinions and their output can not be interpreted easily.

To assess risk of failure for sewer pipelines from which decision regarding inspection frequency and rehabilitation policies are made, McDonald and Zhao (2001) employed factors such as size, location, soil type, buried depth and whether a pipeline is used in combined or separate drainage to assess risk of failure for large diameter sewer pipelines. To calculate the overall impact of failure using the considered factors weighted average was used based on the relative importance weights of each factor. This risk assessment model resulted in low, medium and high impact. In the same context, risk factors with different levels (i.e. 1- 3 and 1 – 5) were used to represent the impact of failure of sewer pipelines (Hintz et al. 2007 and Halfawy et al. 2008). Factors such as: pipe size, effluent type, soil type, buried depth, street category, traffic volume and development future plans in the premises of failed sewer pipelines were studied. The product of the different risk factors and likelihood of failure index which was considered as the ratio of current age to the pipeline's service life; yielded a risk index indicating the impact of failure. In another research by Hahn et al. (2002), knowledge based expert system was used using BBN as inference engine to combine the likelihood and consequences of failure. Structural defects, interior corrosion, exterior corrosion, erosion, infiltration, and operational defects were used in predicting the likelihood of failure, whereas socioeconomic and reconstruction impacts were used in predicting consequences of failure. Experts were sought to determine the impact of the different factors that were adopted from the Water Research Center - Sewage Rehabilitation Manual (SRM) (WRC 2001) on the sewer pipeline. Fuzzy systems and fuzzy set theory were used to combine both the likelihood and consequences of failure (Kleiner et al. 2004; Salman 2010). Possibility, consequences and risk of failure were all described using fuzzy systems from which possibility and consequences of failure were combined using fuzzy rules to determine the risk of failure (Kleiner et al. 2007). Similarly, Salman (2010) used three methods for combining the likelihood and consequences of failure which were multiplication, risk matrix and Mamdani fuzzy inference system (Mamdani and Assilian 1975) to map out sewer pipelines' risk of failure. To determine the likelihood of failure, logistic regression technique was used using pipeline characteristics such as: pipe diameter, slope, length, material, depth and function for an existing sewage network pipelines in USA. The consequences of failure were determined using weighted scoring method by employing sixteen performance indicators for which their relative importance were identified using experts' opinions. In another research to prioritize rehabilitation in sewer pipelines projects, Ana (2009) used ORESTE to develop a priority list from which a decision can be made regarding rehabilitation activities. Different statistical and artificial intelligence techniques such as artificial neural networks, discriminant analysis, survival function and Markov chains were used to determine the likelihood of failure. The relative importance of the different performance indicators such as structural, hydraulic, environmental, social and coordination along a given score for each were used to determine the priority list. In an attempt to develop a risk assessment tool for sewer pipelines, Seattle public work authorities in USA deployed the multiplication method to determine risk of failure (i.e. multiplied likelihood and consequences of failure) (Martin et al. 2007). Weibull distribution (Fréchet 1927) was used to generate probability curves using information from previously failed sewer pipelines obtained from closed circuit television inspection reports for sewer pipelines based on the same material cohorts (i.e. pipelines with the same characteristics). Costs of replacement and repairs were used to determine the consequences of failure with adjustment factors to account for the different economic changes with respect to time. Although the previously discussed models provide the user with versatile risk assessment tools, some assumed that the consequences of failure is known beforehand, in addition some others resulted in more conservative results when compared to actual case studies due to the difference between human judgement and the algorithms used in the techniques used (BBN). Additionally, formulation of certain models such as the one using BBN required large effort to elicit information from experts. Also, some models neglected the operational condition while some others considered that pipelines with the same characteristics would have the same behavior with respect to time.

This paper proposes a methodology that integrates both the likelihood and consequences of failure to assess risk of failure for sewer pipelines. To determine the likelihood of failure both the defects that could be found in sewer pipelines and some pipeline characteristics are used to develop a deterioration model from which pipeline condition at a certain age could be identified. The consequences of failure is studied from an economic loss point of view by using cost benefit analysis in which the different direct and indirect costs as a result of failure and health benefits from avoiding such failure are considered. Because risk yielding from multiplication method is unable to distinguish between low likelihood associated with high consequence of failure and high likelihood associated with low consequence of failure for which the course of action in the two cases might be totally different, it is envisaged that fuzzy inference system would be more appropriate to determine the risk of failure values. Sugeno fuzzy inference system (Sugeno and Kang 1988) is used to combine both components because of its computational efficiency and the suitability of integrating it with different optimization algorithms which are heavily used in decision making in asset management. The resulting risk map is anticipated to help municipalities in identifying sewer pipelines susceptible to failure and would assist in better planning for inspection programs especially in cases of limited funds.

## METHODOLOGY

The methodology adopted in this research is shown in Figure 1. Risk of failure for sewer pipelines was determined by combining two sub-models, namely the likelihood and consequences of failure using Sugeno Fuzzy Inference System (S-FIS). To determine the likelihood of failure Dynamic Bayesian Network (DBN) was used to develop a time dependent deterioration model using the different structural and operational defects that could be found in sewer pipelines and the different pipeline characteristics using the information found in Closed Circuit Television (CCTV) inspection reports for an existing sewage network in Doha, Qatar. The first step to develop the DBN model was to use the different defects in constructing a static

Bayesian Belief Network (BBN) which was considered as inference engine. Logistic regression was used to determine the temporal links (i.e. transitional probabilities) to introduce the time dimension in the deterioration process of sewer pipelines. Consequences of failure was determined by identifying the different costs resulting from failure of sewer pipelines. Direct costs paid to reinstate failed sewer pipelines and indirect costs such as traffic disruption, delays to and absences from work related costs were included. A what-if scenario was assumed to determine the benefits of avoiding failure of sewer pipelines from which benefits to the human and health sector were identified in terms of monetary amounts. The consequences of failure was indicated using the cost benefit ratio. The different levels of likelihood and consequences of failure were represented on a fuzzy scale with the corresponding membership values, then using base of rules, a risk map was developed indicating the risk of failure level. The proposed risk assessment tool was integrated in ArcGIS environment from which users and experts can determine the risk of failure based on the risk index of each pipeline. The tool was tested with actual inspection data from which the resulting prioritized inspection list was compared to the actual inspection list.

**Figure 1**

## ASSESSING RISK OF FAILURE FOR SEWER PIPELINES

Likelihood and consequences of failure are combined to assess the risk of failure of sewer pipelines, from which the adverse effects of the asset's failure can be avoided. By combining these two components the resultant can truly represent the users' interpretation and perception of risk. To determine the different condition ratings of sewer pipelines with respect to time, deterioration models are usually used. Due to the uncertainties accompanying estimating the costs resulting of failure of sewer pipelines, determining the consequences of failure component could be complex. As such, alternative concepts such as economic loss models can be used because it can provide a global and generic framework to calculate the costs as a result of asset failure (Kelly, 2015). The following sections provide a description for the development of the likelihood of failure, consequences of failure and risk assessment models.

## Likelihood of Failure

Deterioration models could provide users with the remaining useful life of sewer pipelines from which likelihood of failure or the probability that a pipeline is in a certain condition state could be determined. In this study, a defect based deterioration model is proposed that takes into consideration the different sewer pipeline defects and some of the pipelines' characteristics. Data extracted from Closed Circuit Television (CCTV) inspection reports for an existing sewage network in Doha, Qatar was used to construct a Dynamic Bayesian Network (DBN). The data comprised 1500 sections of inspected pipelines with a total length of 30 km. Data such as pipelines diameter, material, depth, length, street name/category, different type of defects, structural condition rating, operational condition rating and overall condition rating were shown in the collected CCTV inspection reports. Condition rating followed the condition code EN13508 (British Standards Institution (BSI) 2012) and class method DWA-M 149-3 (German Association for Water, Wastewater and Waste (DWA) 2015) with a scale of 0 to 4, where 0 indicating an excellent and 4 indicating a critical condition for the pipeline.

### *Bayesian Belief Network (BBN)*

To develop a DBN, static BBN was first constructed as an inference engine between different defects and the condition rating of the sewer pipelines as shown in Figure 2. The different structural defects such as: cracks, fractures, physical damages and surface damages, in addition to the different operational defects such as: infiltration, roots, soil intrusion, services intrusion and deposits and their respective subtypes were included in the formulated BBN. Each of these defects was represented by three states which were: light, medium and severe. The different defect sizes and lengths were transformed into these linguistic terms using thresholds values adopted from Rahman and Vanier (2001). The probability of occurrence of different defects with different states was observed from which the marginal probabilities required in the BBN formulation was determined. To determine the conditional probabilities for the different defects with respect to the different condition ratings (structural, operational and overall), log-likelihood algorithm was used in the parameter learning process. Table 1 shows a sample for the marginal probability of defects and the conditional probability of structural condition rating in case of fracture defects.

**Figure 2**

**Table 1**

***Dynamic deterioration model using BBN***

Because deterioration process is dynamic in nature and time dependent, static BBN was converted into a dynamic network by introducing time dimension (i.e. DBN) using transitional probabilities. DBN comprises several BBNs in different time steps that are connected with temporal links also known as transitional probabilities. Multinomial Logistic regression was used to determine the transitional probabilities by employing pipeline characteristics which included: age, diameter, length, buried depth, street category and material type as explanatory variables, while structural and operational condition ratings were considered as dependent variables. Equation 1 shows the general form for the structural and operational condition rating for sewer pipelines using multinomial logistic regression.

$$Ln\left(\frac{P(x,y=i)}{P(x,y=3)}\right) = \alpha_j + \beta_{j1} * A + \beta_{j2} * D + \beta_{j3} * L + \beta_{j4} * d + \sum_{l=5}^{7} \sum_{k=1}^{3} \beta_{jl} * Z_{Street=k} + \sum_{l=8}^{14} \sum_{k=1}^{7} \beta_{jl} * Z_{mat=k} \quad (1)$$

Where $x, y$: the structural and operational condition rating of sewer pipelines , $j$: 1, 2 indicating the condition ratings, A: age, D: diameter, L: length, d: buried depth, $\beta_{j1}, \beta_{j2}, \ldots\ldots \beta_{j14}$: regression coefficients estimated by the maximum likelihood method for condition rating (j), $Z_{Street}$ and $Z_{mat}$ are variables representing the street category and material of pipelines in which $k = 1$ for Asbestos Cement (AC) pipes and/or primary street category, $k = 2$ for Vitrified Clay (VC) and/or secondary street category, $k = 3$ for Polyvinyl Chloride (PVC) and/or local street category, $k = 4$ for Reinforced Concrete (RC) pipes, $k = 5$ for Brick pipes, $k = 6$ for Concrete pipes and $k = 7$ for Glass Reinforced Plastic (GRP) pipes. Table 2 shows the parameter estimates for the various independent variables coefficients$(\beta)$. To test the significance of the developed model $(p)$ value was set $\leq 0.05$ in which independent variables having a $(p)$ value greater than 0.05 were considered statistically insignificant.

**Table 2**

The resulting equations from using multinomial logistic regression could determine the probability of the structural or operational condition rating of a pipeline based on indirect assessment. The rate by which a defect - either structural or operational - propagates (i.e. light to medium or medium to severe) with respect to time was assumed to be the same as the rate by which the pipeline's condition deteriorates. Figure 3 shows a sample for the probability of the structural condition rating with respect to age by using Equation 1 resulting from multinomial logistic regression analysis and the resulting deterioration curves by using the proposed DBN. Using the two deterioration curves, the probability of different condition ratings (structural, operational and overall) at which a pipeline would reach at a given year could be identified. The dynamic deterioration model was validated using actual data for an existing sewage network in Doha. The values for the Mean Absolute Error (MAE) in the static BBN model was 0.67, 1.06 and 0.56 for structural, operational and overall condition rating, respectively. Additionally, to validate the DBN, the year at which a pipeline would enter a certain condition was compared with the actual year and it was found that there is a deviation of ±5-10 years. More can be found on the model development and validation of the developed dynamic deterioration model in Elmasry et al. (2017)

**Figure 3**

## Consequences of Failure

Estimating the costs of failure of sewer pipelines is accompanied with uncertainties which could be avoided by using economic approaches such as economic loss models (Salci and Jenkins 2016). To determine the consequences of failure component in the proposed risk assessment model; Cost Benefit Analysis (CBA) approach was used in which different direct and indirect costs as a result of sewer pipelines' failure were analyzed. Additionally, benefits that could return on both health sector and individuals were converted into cost utilities by assuming a what-if scenario for failure of sewer pipelines and considering that failure was avoided leading to better sanitation services (Prieto and Sacristán 2003). Using CBA could model the economic loss between the baseline scenario (case of no failure) and post disaster scenario (case of failure) from which the economic loss would indicate the impact of failure. In the following section the different costs and benefits included in the CBA are described.

### *Costs of failure*

Direct costs of failure are defined as all the costs that can be easily identified and paid to reinstate failed sewer pipelines and include costs of labor, equipment and material. The second classification of costs are the ones borne by the society. These costs may include loss of businesses, traffic disruption, soil and ground water quality degradation and others (Allouche et al. 2000). Equation 2 represents the direct costs resulting from failure of sewer pipelines, whereas Equation 3 represents the indirect costs included in estimating the consequences of failure for sewer pipelines.

$$D.C. = C_{mat} * (L) + (\sum_{i=1}^{n} C_{Resi} + \sum_{j=1}^{m} C_{Equj}) * (D) + C_{AC} \quad (2)$$

Where, $D.C.$ are the direct costs as a result of failure, $C_{mat}$: cost of pipeline material per unit length, $L$: length of pipeline to be reinstated, $C_{Res}$: hourly cost of labor of type $(i)$ with a total number of (n), $C_{Equ}$: hourly cost of equipment $(j)$ with a total number (m), D: duration of reinstatement works (hours) and $C_{AC}$: Administrative and project management costs (5-10% of the direct costs).

$$I.C. = C_{Traf} + C_{Econ} \quad (3)$$

Where, $I.C.$: are the indirect costs borne by the society as a result of sewer pipelines failure, $C_{Traf}$: Costs related to traffic disruptions and $C_{Econ}$: costs related to loss of productivity and delays to work. The costs as a result of traffic disruption include but are not limited to: over consumption of fuel due to congestion, cost of time loss due to traffic diversions, additional cost due to additional traveling distance and cost of lost parking spaces. The models developed by Gourvil and Joubert (2004); Rahman et al. (2005); Pucker et al. (2006) were adopted to calculate these costs as shown in Equation 4.

$$C_{Traf} = [(\sum_{i=1}^{N}(Con_{dis}^{i} - Con_{nor}^{i}) * n_v^i ) * \ f_c * d + (N_{na} * c_p \ * \ o.r.* \ t_O) \ + (\sum_{i=1}^{N} c_v^i * \ n_v * d_a)] \ * D \quad (4)$$

$Con_{dis}^{i}$: Average consumption of vehicles of type ($i$) during disruption (Liter/km), $Con_{nor}^{i}$: Average consumption of vehicles of type ($i$) during normal cases (Liter/km), $n_v^i$: Number of vehicles of type ($i$), $f_c$: Fuel price ($/Liter), $d$: Disruption distance (km), $o.r.$: Rate of occupancy (%), $N_{na}$: Number of non-accessible parking spaces, $c_p$: Hourly Cost of parking ($ / h ), $t_O$ : Number of operating hours per day (h / day), $d_a$: Additional distance, $c_v^i$: Running cost per Kilometer for vehicle of type ($i$) ($/km), $n_v$: Number of vehicles impacted per day (vehicles/day), N: the total number of vehicles of different types. Construction works carried out to reinstate failed sewer pipelines could affect businesses and employees in work spaces which could be translated into costs. The noise as a result of construction works and traffic disruption could result in reduction of employees' productivity and absences from or delays to works, respectively as shown in Equation 5.

$$C_{Econ} \ = \ D \ * [\sum_{i=1}^{N}\left(R.F.* r_h^i * n_i\right) + \ \sum_{i=1}^{N}(r_h * \ n_i * t)] + \ \sum_{i=1}^{N}(n_v^i * \ o.r.* r_h^i) * t_d \quad (5)$$

Where, R.F.: Reduction factor for worker's (i) productivity ranging between 0.65 to 0.9 based on noise levels, $r_h$: Average hourly rate of employee of type (i) ($/hour) , $n_i$: Number of employees of type ($i$), $t$: delays to work as a result of construction works (hours) and $t_d$: time lost due to traffic diversion.

***Benefits of avoiding failure***

Avoiding failure of sewer pipelines could be considered beneficial to health and individuals (WHO 2001). In the proposed CBA model, benefits from avoiding failure of sewer pipelines were analyzed in which the different utility costs as a result of avoiding such failure were estimated as per Equations 6 and 7. These costs include the costs borne by the health sector for offering treatment for probable infected cases. In addition to these costs, there are transportation costs paid by individuals to receive treatment and costs involved due to individual’s illness such as costs of absences from or delays to works.

$$B_H = n_{inf} * [(0.92 * C_{trea} * D_{Out}) + (0.08 * C_{trea} * D_{In})] \tag{6}$$

Where, $B_H$: Benefits on the health sector, $n_{inf}$: Number of cases (usually taken 14% of the population served by the pipeline (WHO 2001)), $C_{treat}$: Cost of treatment for inpatients and outpatients, $D_{In}$ and $D_{Out}$: are the durations the patient would spend in clinic or hospital to receive treatments (usually taken 1 and 5 days for inpatients and outpatients, respectively (WHO 2001)).

$$B_{Ind} = n_{inf} * [C_{tran} + p_{hr} * (0.92 * D_{Out} + 0.08 * D_{In})] \tag{7}$$

Where, $B_{Ind}$: Benefits on individuals, $C_{tran}$: transportation cost, $p_{hr}$: patients hourly rate

***CBA for failure of sewer pipelines***

To carryout CBA, several approaches can be followed such as determining the Internal Rate of Return (IRR) or Net Present Value (NPV) and Cost to Benefits Ratio (CBR). In this research CBR was used to represent the level of failures in which all the previously costs were combined in one equation as shown in Equation 8.

$$\frac{C}{B} = \frac{\sum_{t=1}^{T} \frac{(D.C.+I.C.)_t}{(1+r)^t}}{\sum_{t=1}^{T} \frac{(B_H+B_{Ind})_t}{(1+r)^t}} \tag{8}$$

Where r: rate to account for time value of money, t: current study year, T: total number of years and ${}^{C}/_{B}$: indicates the level of failure (${}^{C}/_{B}$ <1 indicates insignificant and $({}^{C}/_{B})$ > 1 indicates catastrophic levels of failure). The accuracy of predicting the consequences of failure was examined by comparing the values obtained from the model and an actual failure case in the city of Gatineau in the province of Quebec in Canada.  It was found that there is a deviation between the calculated and actual values ranging between 12% for direct costs and 30% for the indirect costs. More about the economic loss model can be found in Elmasry et al. 2017b.

**Figure 3**

**Risk Assessment Using Sugeno Fuzzy Inference System (S-FIS)**

Combining likelihood and consequence of failure components to assess risk of failure can be performed using multiplication, risk matrices and Fuzzy Inference Systems (FIS). FIS are considered better than the other two approaches because of their flexibility when assigning different values for likelihood and consequences of failures. FIS have the ability to group likelihood and consequences into discrete ordinal groups and assigning risk values for each combination (Salman 2012). Additionally, FIS can determine the resulting risk value more accurately when a pipeline lies near the cut off values of two different ordinal groups which could cause loss of information. By categorizing the probability and consequences of failure in ordinal groups (Extremely Low, Very Low, Low,…,etc) and assigning risk to the different combinations, decision makers are provided the flexibility to determine the risk of failure under different scenarios. One of the challenges in doing so is determining the cut-off values because each linguistic value is translated under different perceptions. Additionally using fuzzy inference system would prevent the loss of information that might be caused as a result of having different set of pipelines under the same ordinal group having different probability and consequences of failure. Also, there may be high differences in terms of the risk values assigned to the sewer pipelines that have similar probability or consequences of failure values but located on different sides of the cut-off points.  Incorporating the fuzzy logic to relate probability and consequences of failure to determine the risk of failure eliminates the above problems while allowing the users to use their experience.  There are two methods for FIS namely Mamdani (Mamdani and Assilian 1975) and Sugeno (Sugeno and Kang 1988). In both methods, crisp inputs are fuzzified using fuzzy sets and fuzzy membership functions, then antecedent statements (i.e. AND or OR operators) are used to determine the area under the consequent fuzzy membership function. The main difference between Mamdani and Sugeno FIS is in the aggregation operation which combines the resulting fuzzy rules. In Sugeno method weighted average is used based on the relative weights of the different output levels, while in Mamdani deffuzification is carried out using different methods. Although Mamdani FIS is the most widely used method in engineering applications, Sugeno method has proven to be more computationally efficient and suitable when combined with other algorithms and optimization techniques. To model risk using FIS, Sugeno method was used because the resultant risk map would usually be optimized to determine the optimal combination for inspection or intervention activities, as such it was deemed more suitable to be used in assessing risk of failure.

Likelihood and consequences of failure were represented on an ordinal scale indicating their different levels. Usually pieces of information handled should be in order of $7\pm2$ (Karwowski and Mital 1986). Therefore, 7 levels were chosen to represent likelihood, consequence and risk of failure to provide the user with more flexibility when expressing the notion of these parameters.  Table 3 shows a matrix for the risk levels adopted in this research. Membership functions could have several shapes such as triangular, trapezoidal, Gaussian and others; Triangular Fuzzy Numbers (TFNs) were chosen in this research because they are suitable for the nature of the proposed model and their simplicity (Lin and Lee 1996). Equation 9 shows the membership functions of likelihood and consequences of failure based on the adopted 7 degree scale.

$$\mu_1^l(x_l) = \mu_1^c(x_c) = \begin{cases} 1 - 7x, & 0 \le x < 0.13 \\ 0, & 0 \le x < 0.13 \end{cases} \quad (G = 1)$$

$$\mu_G^l(x_l) = \mu_G^c(x_c) = \begin{cases} 0, & 0 \le x < \frac{G-2}{6} \\ 7x - (G-2), & \frac{G-2}{6} \le x < \frac{G-1}{6} \\ G - 7x, & \frac{G-1}{6} \le x < \frac{G}{6} \\ 0, & \frac{G-1}{8} \le x < 1 \end{cases} \quad (G = 2,3,4,5,6) \tag{9}$$

$$\mu_7^l(x_l) = \mu_7^c(x_c) = \begin{cases} 0 & ,0 \le x < 0.85 \\ 7x - 6, & 0.85 \le x < 1.0 \end{cases} \quad (G = 7)$$

Where $\mu_1^l(x_l), \mu_G^l(x_l), \mu_7^l(x_l), \mu_1^c(x_c), \mu_G^c(x_c), \mu_7^c(x_c)$ are the membership functions of likelihood and consequence based on the different grades (i.e. scales) (G) of the fuzzy numbers, and $x_l$ and $x_c$ are the latent uncertain variables for likelihood and consequence, respectively. Figure 4 shows the different membership functions for both likelihood and consequences of failure.

**Figure 4**

In the proposed risk assessment model, likelihood and consequence of failure were considered the input while the risk of failure was considered the output. The relationship between the input and output variables were represented in the form of if then rules as shown in Equation 10.

$$F_i: if\ x_i\ is\ A_i\ and\ x_j\ is\ A_j, then\ y\ is\ B_{ij} \tag{10}$$

Where, *Fi* is the fuzzy relation, $x_i$ and $x_j$ are the inputs (antecedent) linguistic variable, $A_i$ and $A_j$ are the input linguistic constants, $y$ is the output (consequent) linguistic variable and $B_{ij}$ is the consequent linguistic constant. Each rule was regarded as a fuzzy relation: $F_i(x \times y) \rightarrow [0,1]$ which was computed by using fuzzy conjunctions. “AND” operator was used in the proposed base of rules in the risk assessment model for which the fuzzy conjunction was “*A*x*B*” computed by a minimum operator as shown in Equation 11:

$$F_i = A_i \times B_i, \ \ \mu_{Fi}(x_i, y) = \mu_{Ai}(x_i) \cap \mu_{Bi}(y) \tag{11}$$

After fuzzifying the inputs, base of rules were used to link the different antecedents with the consequent. Figure 5 shows a risk map developed for the different 49 base of rules resulting from the 7 levels of the likelihood and consequences of failure.

**Table 3**

**Figure 5**

## A TOOL FOR PRIORTIZING INSPECTION OF SEWER PIPELINES

To automate the proposed risk assessment model, an algorithm to calculate risk using S-FIS was implemented using python programming language with the aid of a special library for functions tailored especially for fuzzy logic called "scikit fuzzy" (Python Core Team 2017) to be integrated in ArcGIS. The algorithm used in Python code included syntax for fuzzy membership function generation, rules generation, fuzzification and deffuzification and exporting the different data from ArcGIS.

Figure 6 shows how the different models and tools collaborate forming the risk indexing automated tool.

**Figure 6**

A python code was created to export the required attributes found in pipeline and roads geodatabases (layers) to perform the calculations for both the likelihood and consequences of failure and then for importing the resulting risk and expected year of inspection back in the ArcGIS file. The pipelines' age, size, material, depth, year of installation, roads' number of lanes and category were the attributes exported from attribute tables in ArcGIS. The different pipeline attributes were exported to MS-Excel from which probability of failure and time at which the pipeline would reach a certain condition state set by the user were identified using the deterioration model. Similarly, the road type and number of lanes were used to calculate the consequences of failure. Using the different risk indices and the year of failure, the proposed tool enables the user to determine the risk index of pipelines. Figure 7 shows a snapshot for a sample of information that are displayed when clicking the developed automation tool bar. Figure 8 shows the required input from the user for the developed tool.

**Figure 7**

**Figure 8**

**Tool Implementation – (Case Study)**

To examine the applicability of the proposed risk assessment model, actual data for inspection reports of a sewage network in Doha, Qatar was used to compare the output of the model with the pipe section's actual inspection dates and order. The data comprised 470 inspected sections with their names along the different defects in each section and the different pipeline characteristics (diameter, material, length, street category and depth). In addition, inspection dates for each section and the order of the inspection was also included in the data. One of the challenges that face municipalities in making decisions regarding inspection, is which sections should be included and their inspection order. Due to the lack of decision support tools, municipalities select sections randomly which would result in unnecessary inspections. Table 4 shows a comparison between the costs resulting from the current inspection practices in the municipality in Doha and the costs resulting in case the proposed tool is deployed. The significant difference in the two costs represents how this tool is expected to reduce unnecessary costs.

**Table 4**

To compare between the actual and calculated costs, a planning horizon of 10 years in which inspection would take place was assumed. It was found that approximately 10 kilometers with an inspection cost of 34,470 USD did not require inspection because condition rating for these pipelines was either excellent or very good and risk of failure was extremely and very low. Additionally, the total costs of inspections were 154,940 USD for the 470 inspected sections. On the other hand, it was found that only 108 sections with a total length of 5570 meters required inspection (condition rating for these sections was between critical and poor and risk of failure was extremely and very high) with a total inspection cost of 34,625USD. By calculating the differences between the actual and proposed inspection costs, it was found that the tool could achieve almost 76% cost savings. Table 5 shows a sample for the proposed inspection order calculated using the proposed tool. The table shows the likelihood, consequences and risk of failure based on the defects and pipeline characteristics. It is obvious from the inspection order that several sections (sections having orders: 110, 172, 261, 302, 412, 422..,etc) were inspected in the years 2013, 2014 and 2015, however they could have waited for several years before they were inspected.

**Table 5**

**Sensitivity Analysis**

To examine the robustness of the proposed risk assessment model, a sensitivity analysis was conducted on 4 cases representing the effect of variability in the confidence of decision maker about the level of failure and consequences. Different scenarios were set in each case to represent the confidence of the decision maker in deciding how likely the failure would take place and its category. The details of these cases and the different scenarios are presented in Table 6. As shown in the table, scenario 1 indicates high failure likelihood (confident decision-maker), whereas scenario 6 depicts a low likelihood of failure (a reluctant decision-maker). The results of the sensitivity analysis are presented in Figure 9. It is obvious that the scenarios related to the likelihood of failure show an exponential decay with respect to risk, whereas the consequences are linear. The fuzzified failure in risk calculations transformed the linear dependency to a non-linear relationship. This means that at a higher failure likelihood (confident decision-maker) it is likely that the risk is high; however, as the failure likelihood decreases (reluctant decision maker), the risk estimates would probably decrease, but at a comparatively slower rate.

**Figure 9**

**Table 6**

## CONCLUSION

This paper presented a tool for assessing risk of failure in sewer pipelines. To develop the tool, two sub-models namely likelihood and consequences of failure were developed. In the likelihood of failure model, deterioration curves were created using different defects that could be found in sewer pipelines and different pipeline characteristics using Dynamic Bayesian Network (DBN). The different defects in addition to the different condition ratings were used to build a Bayesian Belief Network (BBN). Multinomial logistic regression was employed using different pipeline characteristics to determine the transitional probabilities required to transform the BBN into DBN. Prediction accuracy of the deterioration model was examined using actual data and it was found that the Mean Absolute Error ranged between 0.56 and 1.06 for the different condition ratings. Additionally, the years at which a pipeline would enter a certain state were compared with the existing data and it was found that the model had an accuracy of ±5-10 years. Economic loss model was used in an attempt to reduce the uncertainties associated with estimating the costs when determining the consequences of failure. Different direct and indirect costs in addition to the different health benefits from avoiding failure of sewer pipelines were included in the consequences of failure sub-model. By implementing the economic loss model on an actual sewer pipeline failure incident in Quebec, Canada; it was found that model could predict the direct and indirect costs with a deviation ranging between 12 and 31%, respectively. The developed two sub-models were integrated using Sugeno fuzzy inference system to create a risk map to map out the different risk level of failures. An ArcGIS tool was developed for the proposed risk assessment model that can enable the user to identify the risk of failure. This tool could also provide the user with an index out of 1 from which he can compare between the risk of failure indices for the different sections. Based on the resulting risk values, an informed decision regarding inspections or suitable interventions can be made. To examine the applicability of the proposed tool, actual data from an existing sewage network in Doha in the state of Qatar was used. The actual inspection costs were compared with the costs from the proposed tool after determining the sections that would require inspection based on the calculated risk indices. Actual inspection orders were compared with the output from the proposed model and it was found that using the proposed tool a 77% cost savings could be achieved. It is expected that the resulting risk map would help key personnel in municipalities in identifying sewer pipelines that require immediate interventions and would assist in better planning for inspection programs especially in cases of limited funds.

## ACKNOWLEDGMENT

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**Table 1: (A) Marginal and (B) Conditional Probabilities in Case of Fracture Defect Used in Bayesian Belief Network Development**

| Type of Fracture / Severity | Light | Medium | Severe |
|---|---|---|---|
| Circumferential | 0.8499 | 0.1470 | 0.0029 |
| Longitudinal | 0.6505 | 0.1126 | 0.2367 |
| Complex | 0.6505 | 0.1126 | 0.2367 |
| Spiral | 0.3326 | 0.3276 | 0.3397 |

| Circumferential | Longitudinal | Complex | Spiral | Fracture Defect | | |
|---|---|---|---|---|---|---|
| | | | | Light | Medium | Severe |
| Light | Light | Light | Light | 0.3194 | 0.4632 | 0.217 |
| Light | Light | Light | Medium | 0.2792 | 0.4377 | 0.2830 |
| Light | Light | Light | Severe | 0.2905 | 0.2384 | 0.4712 |
| Light | Light | Medium | Light | 0.3333 | 0.3333 | 0.3333 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| Severe | Severe | Medium | Severe | 0.3333 | 0.3333 | 0.3333 |
| Severe | Severe | Severe | Light | 0.4276 | 0.4328 | 0.1394 |
| Severe | Severe | Severe | Medium | 0.4270 | 0.4321 | 0.1408 |
| Severe | Severe | Severe | Severe | 0.4284 | 0.4338 | 0.1376 |

**Table 2: Multinomial Logistic Regression Coefficients for Structural and Operational Condition Rating for Sewer Pipelines**

| | Variables | β (SC=1) | β (SC=2) | β (OC=1) | β (OC=2) | p (SC=1) | p (SC=2) | p (OC=1) | p (OC=2) |
|---|---|---|---|---|---|---|---|---|---|
| | Intercept | 6.348 | -4.296 | -7.431 | -5.052 | 0 | 0.007 | 0 | 0.017 |
| | Length | -0.019 | -0.009 | -0.016 | 0.001 | 0 | 0.048 | 0 | 0.07 |
| | Diameter | 0.001 | -0.002 | 0.001 | -0.002 | 0.077 | 0.036 | 0.2 | 0.109 |
| | Age | -0.085 | 0.072 | 0.167 | 0.089 | 0.005 | 0.023 | 0 | 0.035 |
| | Depth | -0.44 | 0.16 | -0.405 | 0.193 | 0.003 | 0.004 | 0.017 | 0.03 |
| Street | Primary | 0.428 | -0.975 | 0.347 | -0.333 | 0.021 | 0.032 | 0.065 | 0.02 |
| | Secondary | -0.234 | -0.645 | -0.476 | -0.831 | 0.067 | 0.009 | 0 | 0 |
| | Local | Reference Level | | | | | | | |
| Material | AC | -0.34 | -0.06 | -0.383 | -0.16 | 0.053 | 0.09 | 0.04 | 0.08 |
| | Brick | 0.847 | -0.539 | -2.267 | -0.379 | 0.131 | 0.04 | 0.001 | 0.06 |
| | Concrete | 1.167 | 0.526 | 0.313 | -0.239 | 0.101 | 0.04 | 0.072 | 0.08 |
| | GRP | 0.34 | -15.749 | -0.409 | -0.231 | 0.03 | 0.09 | 0.038 | 0.07 |
| | PVC | 17.583 | -0.349 | -1.123 | 0.424 | 0.02 | 0.1 | 0.1 | 0.05 |
| | RC | 1.653 | 0.432 | 0.083 | 0.411 | 0 | 0.03 | 0.13 | 0.05 |
| | VC | Reference Level | | | | | | | |

**Table 3:** Color Coded Risk Matrix Used in Fuzzy Inference of Risk

| Likelihood / Consequence | Insignificant | Very low | Low | Medium | High | Very high | Catastrophic |
|---|---|---|---|---|---|---|---|
| **Extremely Low** | Extremely Low | Very Low | Very Low | Low | Low | Medium | Medium |
| **Very low** | Very Low | Very Low | Low | Low | Medium | Medium | High |
| **Low** | Very Low | Low | Low | Medium | Medium | High | High |
| **Medium** | Low | Low | Medium | Medium | High | High | Very High |
| **High** | low | Medium | Medium | High | High | High | Very High |
| **Very high** | Medium | Medium | High | High | Very High | Very High | Extremely High |
| **Extremely high** | Medium | High | High | Very High | Very High | Extremely High | Extremely High |

**Table 4:** Cost Comparison between Actual Inspection and Proposed Inspection Costs

| CCTV Sewer Inspection | Unit Cost ($ / Meters) | Inspected Section Length (m) | Actual Costs of Inspected Sections (USD) | Costs of Proposed Inspected Sections (USD) |
|---|---|---|---|---|
| 150mm – 200mm | 3.00 | 10,049 | 30,146 | 189 |
| > 200mm – 300mm | 5.00 | 16,356 | 77,681 | 93 |
| > 300mm | 7.50 | 8,766 | 47,112 | 307 |
| Mobilization (Lump Sum) | 6,000 | | | |

**Table 5:** Risk of Failure Indices with Corresponding Proposed Inspection Dates

| Section | Inspection Number | Inspection Date | Length | Diameter | Material | Actual cost of inspection | Proposed Inspection Date | Risk of Failure (Overall Condition ≥ 3) |
|---|---|---|---|---|---|---|---|---|
| 15 A22 9A - 15 A22 9 | 1 | Jan-2013 | 44.60 | 150 | VC | 133.81 | 2035 | 0.751 |
| 15 A22 12 - 15 A22 11 | | | 49.40 | 150 | VC | 148.20 | 2055 | 0.516 |
| 15 A18 - 15 A17 | | | 83.95 | 150 | VC | 251.87 | 2050 | 0.677 |
| 15 A22 9 - 15 A22 8 | 2 | | 22.91 | 150 | VC | 68.73 | 2050 | 0.605 |
| 15 B7 - 15 B6 | | | 35.18 | 150 | VC | 105.56 | 2045 | 0.522 |
| 15 A22 8 - 15 A22 7 | 3 | | 53.54 | 150 | VC | 160.62 | 2043 | 0.516 |
| 15 A16A - 15 A16 | | | 14.32 | 150 | VC | 42.96 | 2067 | 0.314 |
| -- | -- | | --- | -- | -- | -- | -- | |
| 16_4_8_2 - 16_4_8_1 | 1 | Feb-2013 | 54.69 | 150 | VC | 164.0743395 | 2052 | 0.633 |
| 9_C4_5_3 - 9_C4_5_2 | | | 81.96 | 450 | VC | 491.7843098 | 2050 | 0.555 |
| 9_C3_9 - 9_C3_8 | | | 66.13 | 500 | VC | 396.8265984 | 2022 | 0.88 |
| 9_C12_7 - 9_C12_6 | 2 | | 40.41 | 300 | VC | 202.0863036 | 2066 | 0.461 |
| 40A_14_4 - 40A_14_3 | | | 43.65 | 300 | VC | 218.2518963 | 2054 | 0.488 |
| -- | -- | | --- | -- | -- | -- | | |
| 16_4_7_3 - 16_4_7_2 | 1 | Mar-2013 | 68.86 | 400 | VC | 413.1764677 | 2051 | 0.613 |
| 16_4_10 - 16_4_9 | | | 57.47 | 150 | VC | 172.4255487 | 2050 | 0.478 |
| 9_C3_11_1 - 9_C3_11 | | | 11.12 | 150 | VC | 33.36105889 | 2060 | 0.246 |
| 9_C3_4 - 9_C3_3 | | | 42.08 | 150 | VC | 126.2542012 | 2052 | 0.503 |
| 9_C12_3 - 9_C12_2 | 2 | | 42.37 | 250 | AC | 211.8982301 | 2055 | 0.364 |
| 40A_13 - 40A_12 | | | 79.05 | 450 | VC | 474.332686 | 2051 | 0.543 |
| 40A_7_6 - 40A_7_5 | | | 48.10 | 150 | VC | 144.3018276 | 2049 | 0.589 |
| 40A_1_12 - 40A_1_11 | | | 70.88 | 150 | VC | 212.6521204 | 2050 | 0.67 |

# List of Figures

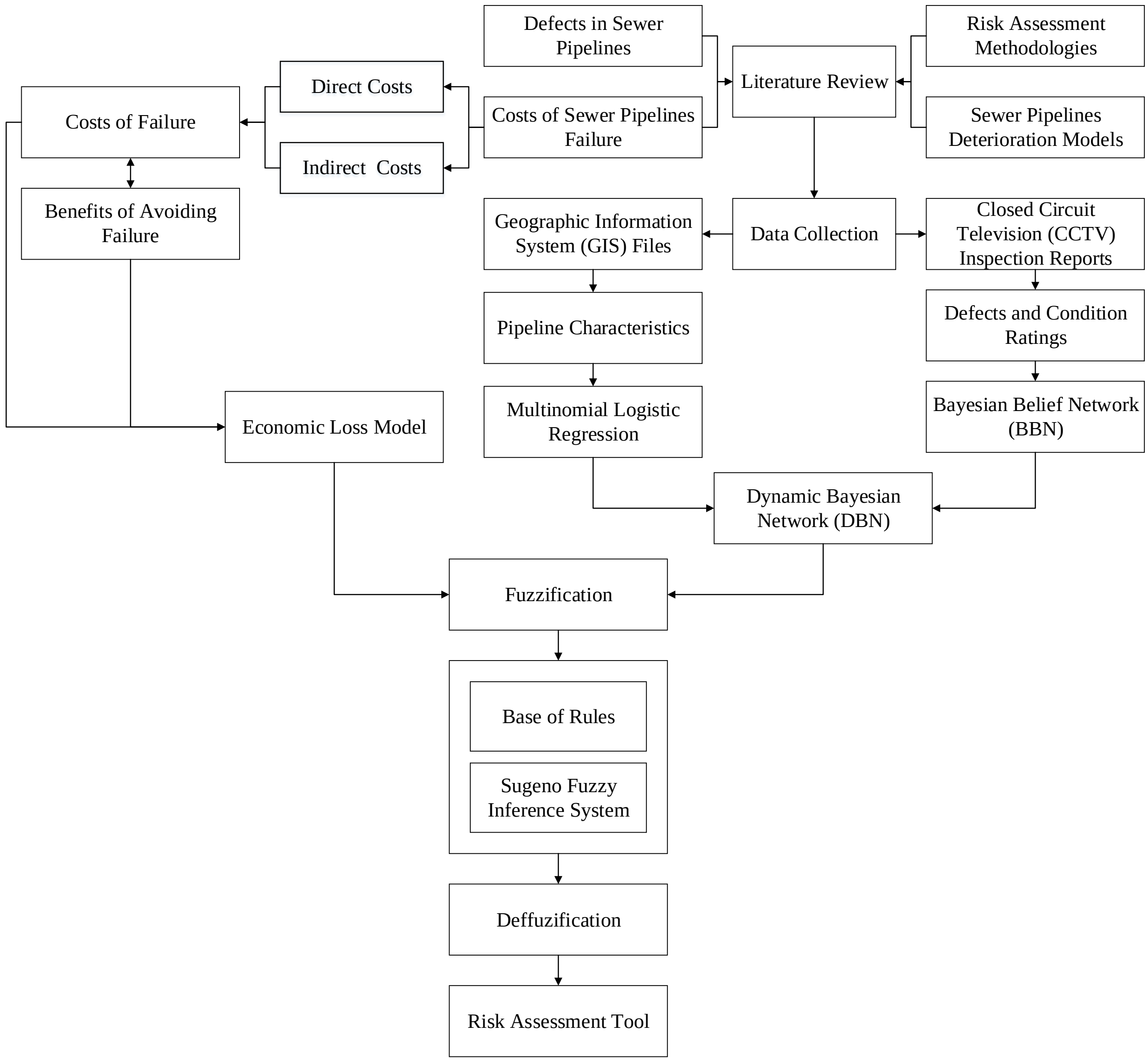



**Figure 1:** Proposed Methodology for the Development of Risk Assessment Tool

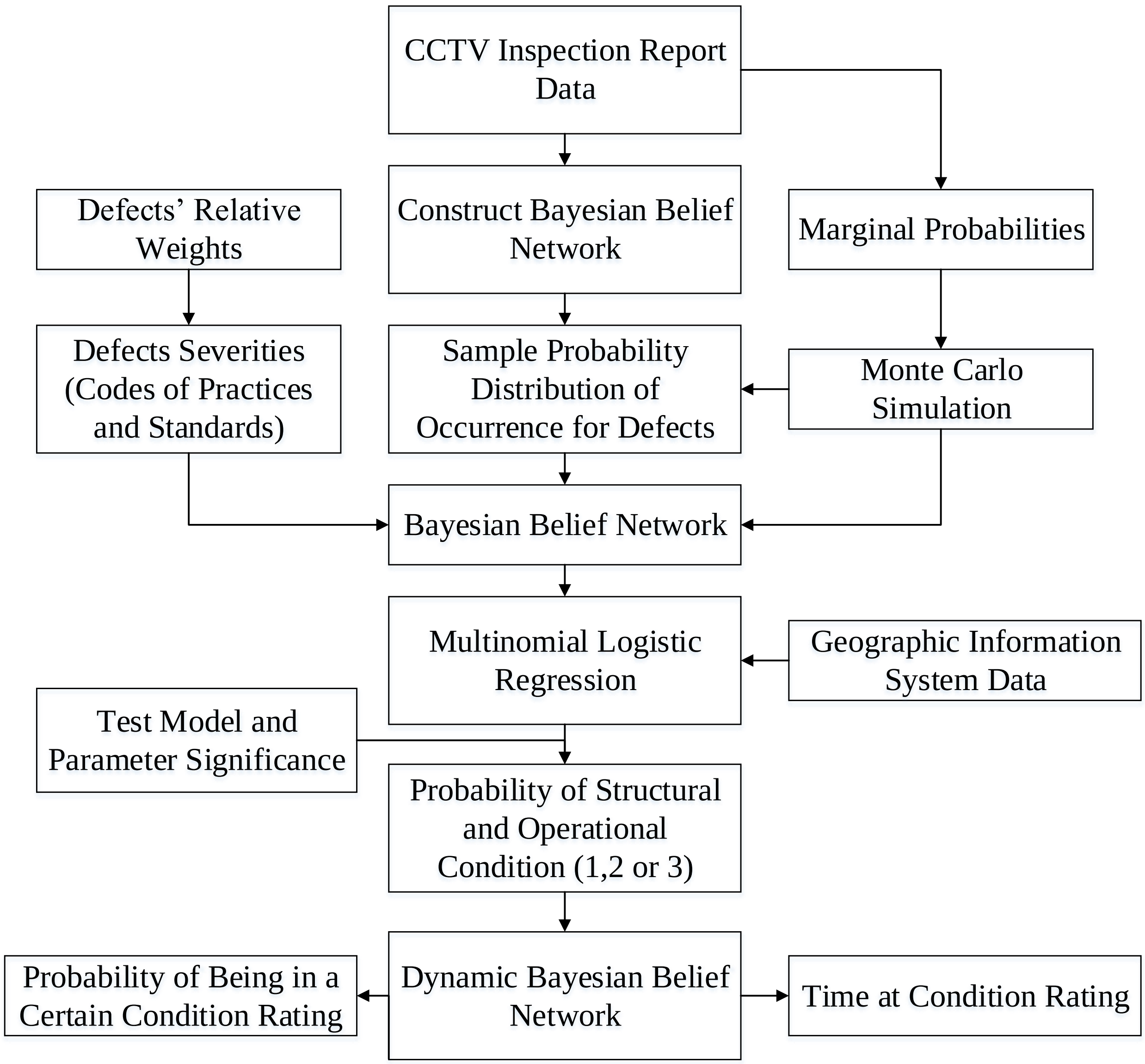



**Figure 2:** Framework for Developing Sewer Pipelines Deterioration Model Using Dynamic Bayesian Belief Network (DBN)

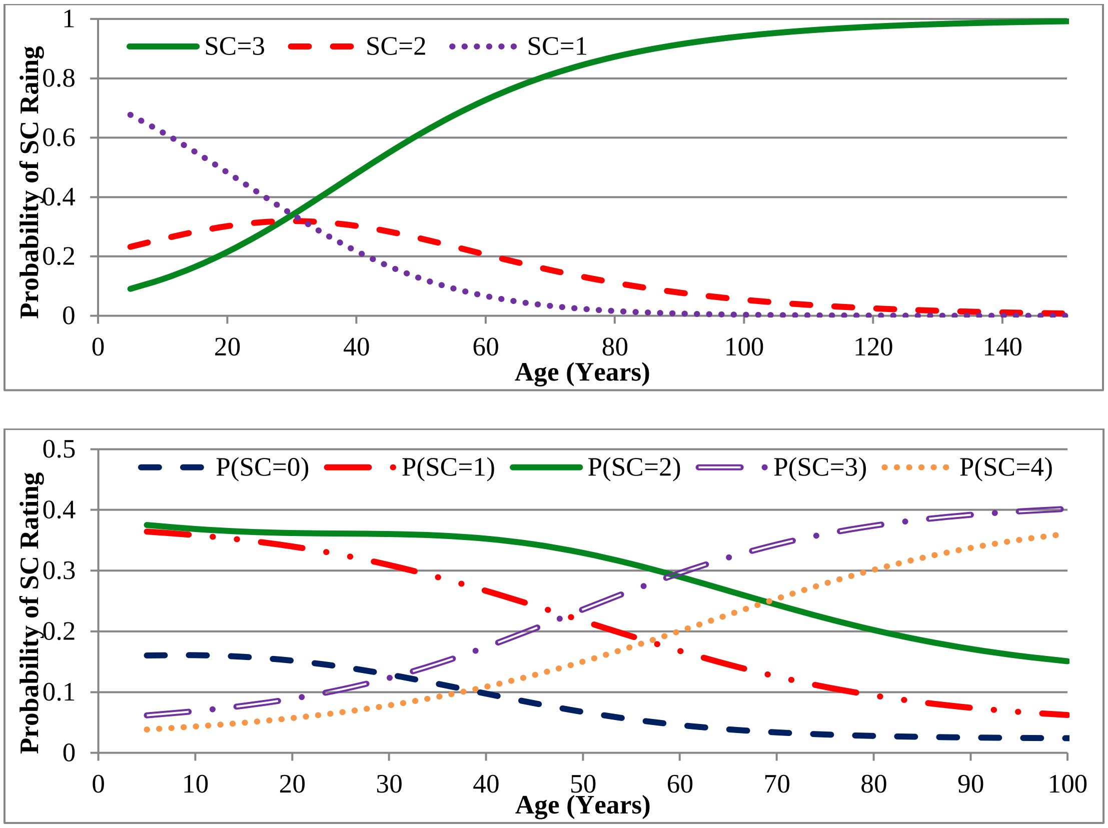
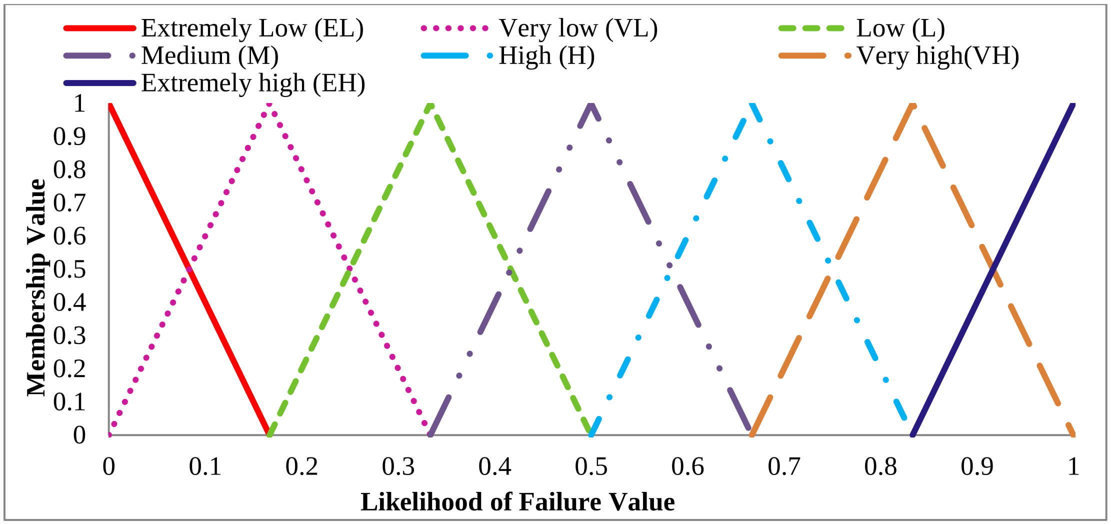



**Figure 3:** Sample for Structural Deterioration Curves of a 200mm Verified Clay Pipe Using Multinomial Logistic Regression and Developed DBN Model



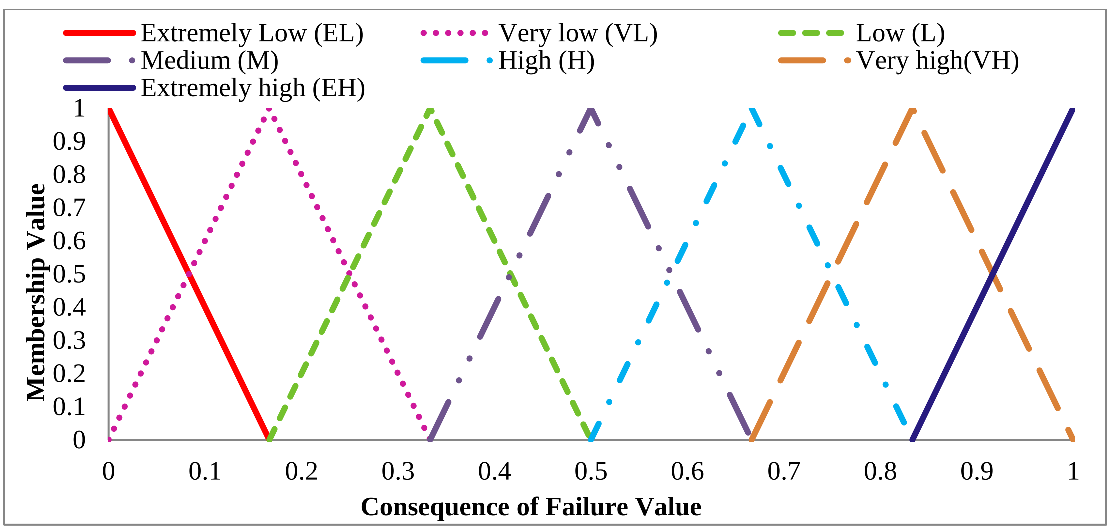




**Figure 4: (A)** Likelihood and (B) Consequences of Failure Levels with Corresponding Fuzzy Membership Values

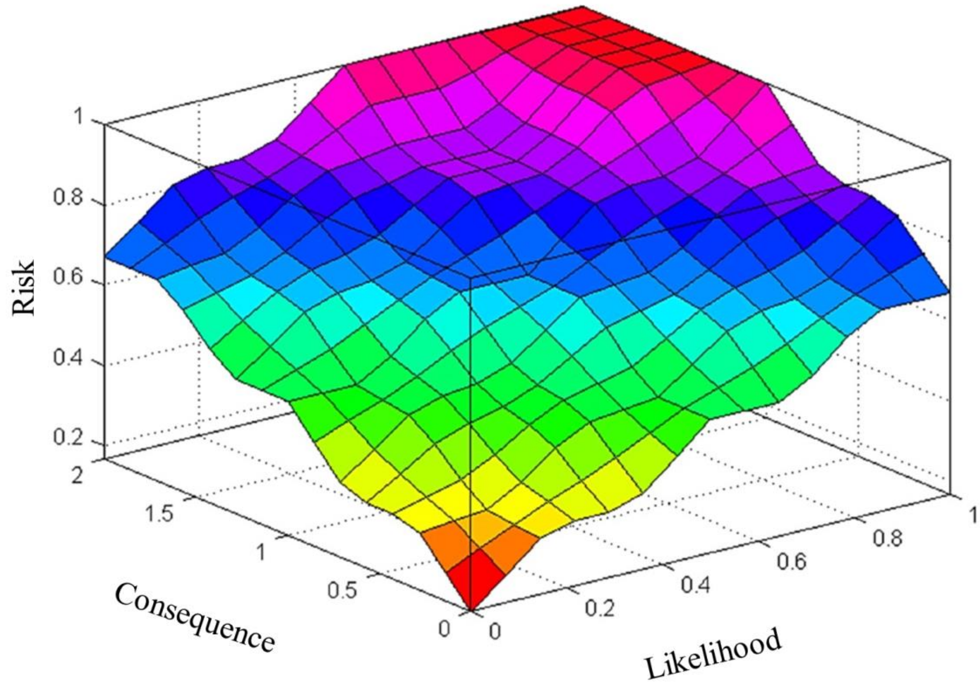



**Figure 5:** Surface of Risk of Failure Using Sugeno Fuzzy Inference System

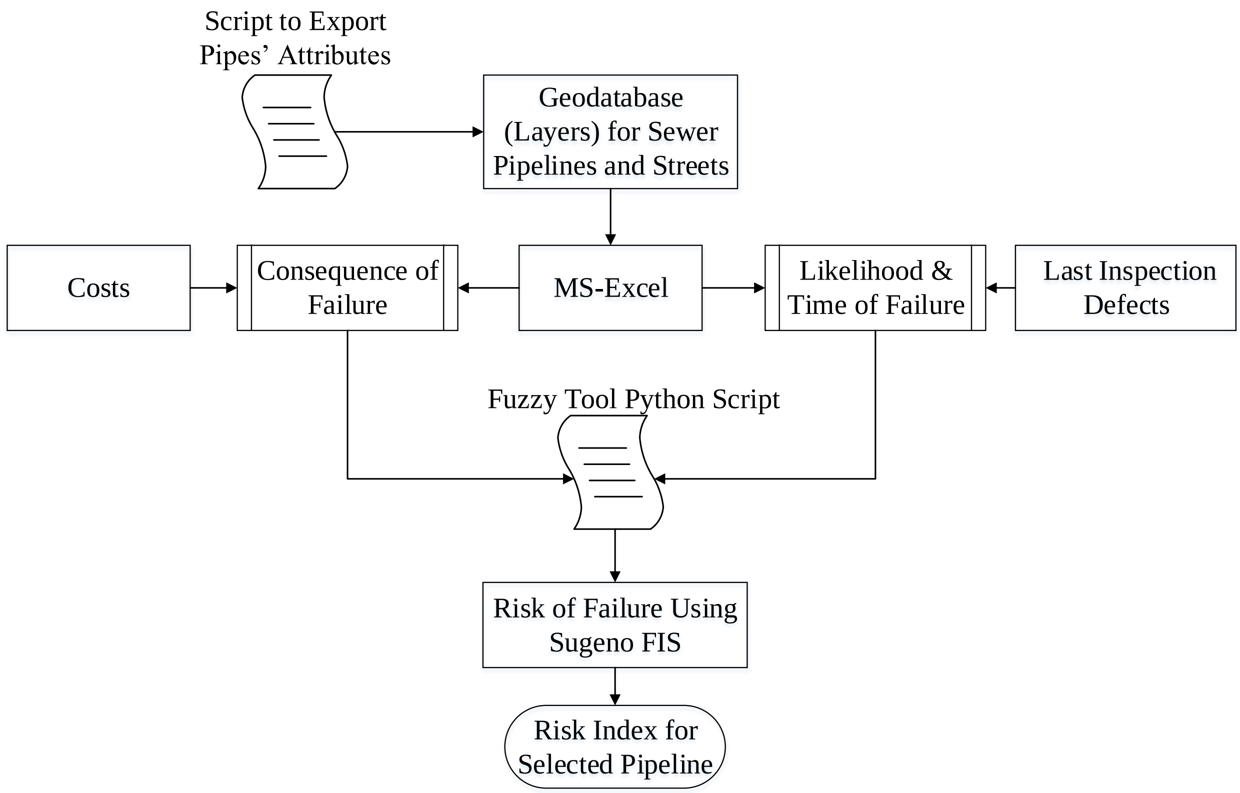



**Figure 6:** ArcMap Add-in Tool to Assess Risk of Failure for Sewer Pipelines' Inspection Prioritization

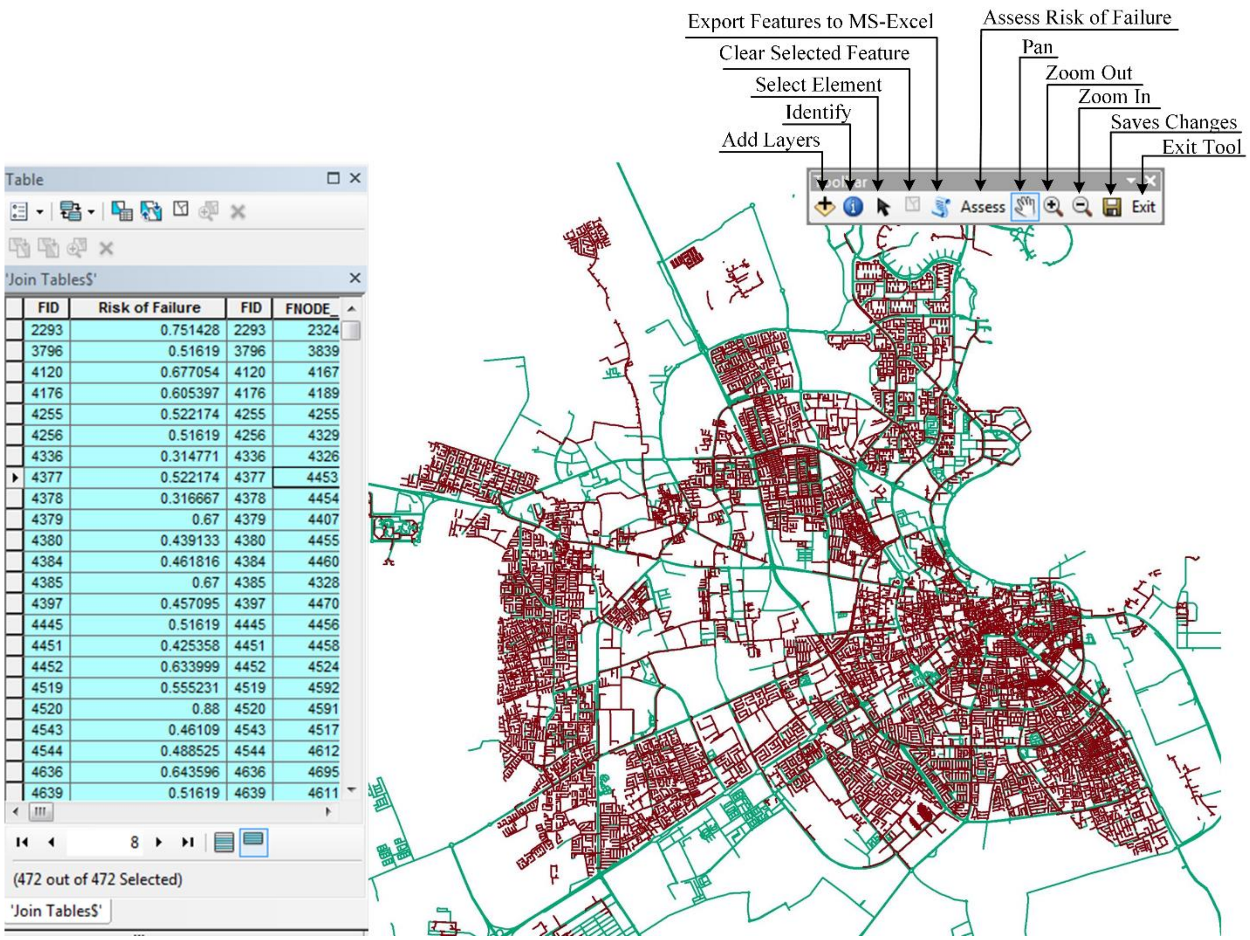



**Figure 7:** Risk of Failure Indicated on Different Sections Using Risk Assessment Tool ArcMap Add-in