

SIMULATION-BASED DETERIORATION PATTERNS OF WATER PIPELINES

By

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ABSTRACT: Water pipelines deteriorate overtime due to several distressing factors. To keep water pipelines in good condition, municipalities need to use reliable and credible deterioration models and inspection plans to better manage their rehabilitation and maintenance. Thus, this paper presents the development of deterioration models and patterns of water pipelines. The deterioration models consider different water pipe sizes and materials as well as different surrounding environmental conditions which affect their deterioration rates. As a prerequisite to the development of such deterioration models, a condition assessment model for water pipelines was first developed. Questionnaires were distributed among experts to determine the weights of the factors affecting water pipeline conditions using the Fuzzy Analytic Network Process (FANP). Monte-Carlo simulation was used to account for the large uncertainties of the calculated weights in the development of the condition assessment model. The validation of the model, which was performed using historical data, yielded an average validity percentage of 93.59%. The developed models are expected to help municipalities and decision makers to accurately plan for future water pipelines maintenance and rehabilitation activities based on their different deterioration patterns. It takes into consideration both the uncertainties at the initial stage and those accumulated during the calculation process.

Keywords: Water Pipelines, Deterioration patterns, Fuzzy Analytic Network Process, Monte-Carlo Simulation.

Acknowledgement: The authors gratefully acknowledge the support provided by Qatar National Research Fund (QNRF) for this research project under award No. QNRF-NPRP 4 - 529 - 2 - 193.

INTRODUCTION

Water distribution pipelines are the most expensive components in a water supply network because of their costs, which represent about 80% of the total expenditure (Giustolisi et al. 2006; Kleiner and Rajani 2000). According to the 2017 ASCE (American Society of Civil Engineers 2017) infrastructure report card, the rating grade for the US drinking water infrastructure is “D”, which indicates a poor condition. The American Water Works Association (AWWA) stated that replacing all US pipelines would cost more than one trillion US dollars. Moreover, the fifth report of the US Environmental Protection Agency (EPA 2013a) reported that a total investment of US\$ 384.2 billion is needed for US water infrastructure during the next 20 years. Approximately 64% of this amount is needed for water distribution infrastructure components. On the other hand, in 2016, around 29% of Canada’s water infrastructure was rated from fair to very poor which was expected to cost CAD\$ 60 billion for their replacement (Canadian Infrastructure Report Card 2016).

The National Guide to Sustainable Municipal Infrastructure best practice stated that a planned inspection program must be developed for water distribution networks in order to minimize public health and safety hazards (Federation of Canadian Municipalities and National Research Council 2003). Deteriorated pipelines endanger public health and safety as well as the environment. To reduce these risks, it is necessary to develop credible deterioration models and an inspection plan for the rehabilitation and maintenance of water pipelines. The deterioration assessment of water pipelines is usually performed using physical-based and statistical approaches. The former checks the physical mechanisms of pipeline failure. However, its drawback is that it requires data, which is either costly or impossible to obtain (Rajani and Kleiner 2001). Thus, physical models can be justified only for major water pipelines due to their large failure cost. On the other hand, statistical

methods can be used for all water pipelines because their input data is less costly and easier to obtain.

The purpose of this paper is to develop deterioration models and patterns of water pipelines. To develop such models, a condition assessment model is to be first developed using an integrated Fuzzy Analytic Network Process (FANP)/Monte-Carlo technique. The model generates a probabilistic condition assessment for water pipelines. It assists municipalities and decision makers in making more accurate judgements and in planning for proper rehabilitation and maintenance activities. The model considers the uncertainties in the initial stages and those accumulated during the calculation process. It also considers three groups of factors affecting water pipeline conditions, namely, physical, environmental, and operational. Questionnaires were distributed among water pipeline experts to collect the data needed to develop the model. The FANP was used to calculate the relative weights of the identified factors. The calculated weights were used as an input in Oracle® Crystal Ball software to obtain a probabilistic condition index for water pipelines using Monte-Carlo simulation. To sum up, the main objectives of the present study are to: 1) identify and study the factors affecting the condition of water pipelines, 2) develop a condition assessment model for water pipelines, and 3) develop different deterioration models for water pipelines considering different pipe sizes and materials as well as different surrounding environmental conditions.

The novelty of this study is in providing two enhanced tools for water infrastructure asset management. The first tool is a condition assessment model for water pipelines that considers interdependency and accumulated uncertainty among the condition predictors to improve the

prediction accuracy. While the second tool is the provision of a condition assessment database that involves all the possible combinations of the different condition predictors' attributes (inputs) along with the predicted condition (output) for each case. Out of this database, hundreds of different deterioration patterns and models for water pipelines can be developed.

BACKGROUND

Several models were developed during the last two decades to assess and predict the condition, failure rate, and deterioration of water pipelines. Kiliç et al. (2018) developed a model to evaluate the technical performance of water pipelines using the Analytic Hierarchy Process (AHP) based on physical, environmental, and operational factors. The model was applied on 17 individual water pipelines and it was determined that the structural condition and performance of asbestos cement and polyvinyl chloride (PVC) pipes was poor and the risk of damage was high. Winkler et al. (2018) used decision tree learning methods to model water distribution pipe failure. The models were trained on 50% of the available data and their performance were evaluated using confusion matrices and receiver operating characteristic curves. The boosted decision tree approach using random under-sampling turned out to have the best performance and thus was applied to a real world case study. Kimutai et al. (2015) presented the development of three statistical models (Weibull proportional hazard model – WPHM, Cox proportional hazard model - Cox-PHM, and Poisson model – PM) to predict pipelines' failure. The models were implemented and tested using water main failure data from the City of Calgary. The testing results showed that WPHM is most suited to predict failures in ductile and cast iron pipelines, while PM is most suited with PVC pipelines. Finally, the Cox-PHM is suitable for failure prediction only in relatively newly installed pipeline systems. A Bayesian Belief Network (BBN) based data fusion model for water mains

failure prediction was developed by Kabir et al. (2015). The model was applied on water main failure data from the City of Calgary. The model can identify the most vulnerable and sensitive pipe in the entire network, as well as the total number of pipes that require immediate and appropriate corrective action. BBN was also used by Francis et al. (2014) to develop pipeline breaks prediction model in drinking water distribution system. The model was trained using historical pipe breaks and covariate data from a mid-Atlantic US drinking water distribution system network. Martins et al. (2013) compared three stochastic models (the single-variate Poisson process, the Weibull accelerated lifetime model, and the linear-extended Yule process) to predict pipeline failures in water supply systems. Consequently, these three models were modified to improve their prediction accuracy and were applied to water supply system data provided by a Portuguese water utility. It was found that the Weibull accelerated lifetime model outperformed the other two models. A weighted factor and fuzzy inference methodology was implemented by Clair and Sinha (2011) to predict the performance index of metallic water pipelines. With the use of continuous membership functions and rule statements, the fuzzy inference methodology was found to be well suited in generating water pipeline performance values over the weighted factor model. Xu et al. (2011) developed two prediction models for water pipelines failure rate using Evolutionary Polynomial Regression (EPR) and Genetic Programming (GP). The results showed that EPR has some advantages over GP in equation uniformity and parameters estimation, while GP was better to find the complex relations. Wang et al. (2010) used a Bayesian inference to assess the condition of water pipelines. Results were modeled by comparing the deterioration rates of the observed and the Bayesian model. The analyses showed that pipe age and diameter had the most influence in determining the pipe condition. A framework to evaluate the failure risk of water main using hierarchical fuzzy expert system was designed by Fares and Zayed (2010). A case study was

applied which classified specific pipe segments based on their risk condition level. Results concluded that small diameter and cast iron pipes contribute most to network risk. Multiple regression models to predict annual break rates of water mains were developed by Wang et al. (2009). A case study utilizing the data of a Canadian municipality water network was implemented to verify the proposed regression models. Zhou et al. (2009) developed a condition assessment model for water pipelines using fuzzy PROMETHEE II. The model processes four first-level and seven second-level pipe condition indicators and then generates a pipe condition index for each pipe in the system. The weight for each indicator was generated using the AHP method. The model was applied to eight pipe samples for testing purposes. Al-Barqawi and Zayed (2008) developed a condition assessment model using integrated AHP/ Artificial Neural Networks (ANN). A case study utilizing three different municipalities in Canada was used to assess the model's performance. Pipe deterioration models for water distribution systems using EPR were developed by Berardi et al. (2008). The case study used involved a water quality zone within a distribution system and entailed the collection of historical data to develop network performance indicators. Economou et al. (2007) developed an aggregated hierarchical Bayesian model for the prediction of pipeline failures. Actual failure data from an underground water pipe network in New Zealand was used to demonstrate the ability of the aggregated model. Achim et al. (2007) developed a multi-layer perceptron neural network to predict pipeline failure in terms of failures/km/year. Results showed higher correlations with recorded data when compared with two previously developed statistical models (shifted time power model and shifted time exponential model) for the same purpose. Multiple linear regression (MLR) and ANN techniques were utilized by Geem et al. (2007) to develop water pipeline condition assessment models. The developed models were applied to a case study in South Korea. The ANN model generated a higher determination

coefficient than the MLR model in terms of the statistical correlation between observed and computed data. Al-Barqawi and Zayed (2006a and b) developed condition assessment models for water mains based on AHP and ANN methods, respectively. Implementing the models on data of water networks from different Canadian municipalities, it was found that the ANN technique outperformed the AHP technique. ANN technique was also applied by Najafi and Kulandaivel (2005) to predict pipelines condition based on historical condition assessment data. Watson et al. (2004) developed a Bayesian-based pipeline failure model. Breaks were generated for two random pipes assuming a constant failure rate to validate the model. The simulation results compared the failure rates vs. time, which illustrated the Bayesian model in comparison with the natural estimation that assumed a Poisson distribution. It was found that the Bayesian model provided a better estimate of the failure rate than the Poisson distribution for the first 25 years after which both methods provided similar estimates. Kleiner et al. (2004) modelled the deterioration of buried pipes using a fuzzy rule-based, non-homogeneous Markov process. This deterioration model yields possibility of failure at every point along the life of the pipe. Geem (2003) used ANN to develop a decision support system for water pipeline condition assessment. The ANN was trained by historical data using back-propagation algorithm. A fuzzy multi-criteria decision-making technique was used by Yan and Vairavamoorthy (2003) for water pipeline condition assessment. Fuzzy set theory has been employed to convert linguistic descriptions of pipe conditions indicator into numerical format. Then using composite programming techniques a screening model was developed that ranks pipes in order of their condition.

The discussed previous studies made an effort in developing models to assess the pipelines' condition and/or predict the pipelines' failure over a time horizon. However, few of these studies

(Wang et al. 2009; Al-Barqawi and Zayed 2008; Al-Barqawi and Zayed 2006b) focused on studying the deterioration patterns of water pipelines with respect to each affecting factor individually, such as the pipe diameter or material. Also, some models did not consider important environmental and/or operational factors in the process of predicting the failure rate of pipelines. Ignoring such factors can affect the robustness of the prediction process. For example, some models considered only the pipe's age, diameter, and length along with historical breakage rate as indicators to predict pipeline failures (Xu et al. 2011; Berardi et al. 2008; Achim et al. 2007). Other models even considered only the pipe's age along with historical breakage rate as indicators to predict pipeline failures (Economou et al. 2007; Watson et al. 2004). Although Yan and Vairavamoorthy (2003) considered both physical and environmental factors to assess pipelines' condition, still they did not consider important operational factors. With respect to models' accuracy, some models were not validated (Francis et al. 2014; Najafi and Kulandaivel 2005; Kleiner et al. 2004), and other models were inadequately validated (Berardi et al. 2008; Geem 2003), while other models provided unsatisfactory validation results (Wang et al. 2009; Economou et al. 2007). Also, the previous studies did not take into account the interdependency between the factors and the uncertainty of their severity weights. For example, Kiliç et al. (2018), Al-Barqawi and Zayed (2008), Al-Barqawi and Zayed (2006a), and Zhou et al. (2009) used the AHP method to determine the weights of the factors affecting pipeline conditions. The AHP method assumes unidirectional relationships between clusters of different decision levels and between clusters neglecting interdependent relationships. This can create dynamics in the form of cause and effect relationships among influential factors, which can severely affect the pipeline condition assessment. Other studies considered the uncertainty of the factors' weights using fuzzy expert

system or Bayesian inference. However, they did not consider the accumulated uncertainties during the process of determining the pipeline condition.

To address the interdependency and accumulated uncertainty among factors, FANP and Monte-Carlo simulation are used in this study to generate more accurate and realistic condition ratings than those obtained using previous models. Moreover, several deterioration models for water pipelines are developed to study the deterioration patterns of different pipe sizes and materials along with other different environmental surrounding conditions with respect to age.

Fuzzy Analytic Network Process

Fuzzy Analytic Network Process (FANP) was used to overcome the limitations of AHP and ANP. AHP does not take into account the interdependencies among the factors used for the assessment process. Although it takes such interdependencies into account, ANP ignores inherent uncertainties and human judgment during the evaluation of the pairwise comparison of the factors. Converting a verbal pairwise comparison judgment into an exact strength ratio of an alternative with respect to another one includes many uncertainties. Therefore, a fuzziness is introduced to ANP to account for these uncertainties. The concept of fuzzy numbers should be incorporated into the ANP to represent the subjective uncertain pairwise judgements (Huang 2012; Lee 2012; Yang et al. 2010; Moeinzadeh and Hajfathaliha 2009).

In this study, FANP is used to determine the weights of the different factors affecting water pipeline condition throughout factors' pairwise comparison. The main aspect is that in FANP the crisp numbers of linguistic evaluation or comparison are replaced with triangular fuzzy numbers.

Many fuzzy pairwise comparison scales such as Cheng's, Kahraman's, Saaty's, or self-defined are currently available (Etaati et al. 2011). Saaty's scale, which is selected herein, recommends adding and subtracting "1" from each response of the pairwise comparison to build the upper and lower matrices, respectively. For example, a response of 5 in the pairwise comparison between two factors P and E will be 4 and 6 in the lower matrix and upper matrix, respectively. Thus, the triangular fuzzy numbers of this comparison case will be 4, 5, and 6 with a membership function of 0, 1, and 0, respectively. Once the fuzzy pairwise comparison is carried, the relative weight of each main and sub-factor is determined throughout defuzzification. Consequently, three supermatrices are constructed in order to obtain the factors' final weights. The first is known as "unweighted supermatrix" which is built using the obtained factors' relative weights. The second is known as "weighted supermatrix" which is built by normalizing each column in the "unweighted supermatrix". Such normalization is done by dividing the corresponding value of each cell in the "unweighted supermatrix" by the summation of its corresponding column. Finally, the third supermatrix to be developed is known as the "limit supermatrix". The "limit supermatrix" is built by raising the "weighted supermatrix" to large powers until the resulting matrix becomes equal to the previous raised matrix (Adams 2001). It is worth to mention that if the "weighted supermatrix" with diagonal cells (intersection of the same factor) of zero is raised to large powers, the "limited supermatrix" converges to a matrix of zeroes, yielding no weights. Thus, the importance of making the diagonal cells equal to one instead of zero is evident. This allows the continuity of the multiplications without converging to zero until the targeted results are reached. The diagonal cells must change only from zero to one for the "sinks", which are the columns with only zeroes in their cells. The columns that will replace "sinks" are called "identity columns". These zero columns or sinks are due to the absence of a relationship between the sub-factors themselves. If a relationship

exists between the sub-factors, the columns will have a value from the pairwise comparison. There are different ways of calculating the “limit supermatrix”. The “Identity at Sinks” method is one of the best methods dealing with the “identity columns” (Adams 2001). The cells’ values of the first column in the “limited supermatrix” after being raised to large powers represent the final weights of the factors.

Monte-Carlo Simulation

A Monte-Carlo simulation approach is used herein to overcome the uncertainty that the responses of the experts generate. Monte-Carlo simulation is a powerful tool that accounts for and quantifies the uncertainty inherited in the models’ inputs. It relies on repeated random sampling and statistical analysis to compute the results (Raychaudhuri 2008). Monte-Carlo simulation can be summarized in the following steps:

1. Define a domain of possible inputs.
2. Generate inputs randomly from a probability distribution over the domain.
3. Perform a deterministic computation on the inputs.
4. Aggregate the results.

RESEARCH METHODOLOGY

The research methodology, which is illustrated in Fig. 1, started by conducting a comprehensive literature review to study the different components of water pipelines systems as well as previously developed condition assessment and deterioration models. After that, the main factors and sub-factors affecting the condition of water pipelines were identified. To verify the adequacy of the selected factors, open-ended (unstructured) questionnaires were designed to allow respondents to

add factors which were not originally included in the survey. Another questionnaire was also developed for two main purposes: (1) perform pairwise comparisons between the main and sub-factors affecting pipeline condition and (2) determine the effect value of each factor characteristic on the water pipeline condition. All the respondents confirmed the suitability of all of the selected factors to assess water pipelines condition. All the pairwise comparisons of the gathered responses were subjected to Saaty's fuzzifying scale as explained earlier. Accordingly, the relative importance weights of the factors were calculated using FANP technique. The probability distributions of the obtained factors' weights along with the determined attribute effect values from the different respondents were fitted. These probability distributions were then used as inputs in the developed water pipeline condition assessment model using Monte-Carlo simulation. The model was validated using actual data from 547 existing water pipelines that was obtained from three municipalities in Canada. A sensitivity analysis was carried out to examine the effect of changing the weight of each assessment factor on the model's output. Finally, the developed model was used to construct a database of predicted pipeline conditions taking into account all possible factor combinations out of which different deterioration models were developed.

CONDITION ASSESSMENT MODEL DEVELOPMENT

It is worth noting that the developed model assumes that the factors affecting the pipe condition are only those which are selected in this study as it will be explained later in the "data collection" section. The developed condition rating model is defined using the following equation:

$$OCI_j = \sum_{i=1}^k W_i \times EV_i \dots \dots \dots (1)$$

Where, OCI_j = overall condition index of water pipeline j ; EV_i = effect value of factor i reflecting the factor score; W_i = final weight of importance for factor i ; and k = number of factors.

The model yields the overall condition index for assessed water pipelines. The higher the index is, the better the pipeline condition is. The overall condition index ranges between the extreme values of 0 and 10 representing the pipeline worst and best conditions, respectively. The worst condition index (i.e., 0) refers to a pipeline that is in a failure state and can no longer operate and fulfill its main function. On the other hand, the best condition index (i.e., 10) refers to a newly installed pipeline having the best physical, environmental, and operational affecting factors. The final weights are calculated using FANP as will be shown later in the model implementation section. The effect values of each factor also range between the extreme values of 0 to 10 representing the pipeline worst and best eligibility, respectively. The assessment model was developed using Oracle® Crystal Ball software. Monte-Carlo simulation was used to randomly generate input variables and consequently assess the output value. The simulated model was developed using the following five steps:

1. The main factors and sub-factors affecting water pipeline condition were identified and analyzed.
2. The final weights (W_i) of each factor were calculated using the received questionnaires and their probability distributions were fitted.
3. The effect values of each factor were also determined using the received questionnaires and their probability distributions were fitted.
4. Equation 1 was used to determine the water pipeline overall condition index (OCI_j).

5. Equation 1 was simulated for several iterations using Monte-Carlo simulation in order to assess the pipeline condition.

DATA COLLECTION

The data collection process was conducted in two main phases. The first phase consisted of identifying the factors that affect the condition of water pipelines. The second phase was concerned with determining the weight and effect values of the factors identified in the first phase.

Phase (1): Factors Affecting Water Pipeline Condition

A comprehensive list of factors affecting water pipeline condition was prepared from the literature (e.g. Fares and Zayed 2010; Wang et al. 2010; Al-Barqawi and Zayed 2008). To check the compatibility of the selected factors, a questionnaire survey was sent to several water main engineers and experts. The questionnaire was designed to be open-ended (unstructured), to allow respondents to add factors which were not originally included. All the respondents agreed that all of the selected factors were adequate to assess water pipelines condition as shown in Table 1. The selected factors shown in the table were grouped into three main categories, namely, physical, environmental, and operational.

It should be noted that other important factors should have been considered when assessing the condition of a pipeline. The final report of the US Environmental Protection Agency in 2013 (EPA 2013b) suggested other factors that are not included in Table 1. For instance, the pipe lining and coating is of an extreme importance for resistance of internal and external corrosion. The existence of such pipeline protection have a significant effect on the pipeline condition. Factors related also

to corrosion are stray currents, oxygen gradient, and bi-metallic connections. Other important factors that can physically affect the pipeline structure include point loads, internal radial loads, axial loads from seismic activity, and thermal stress from temperature differences between water, pipe, and soil (EPA 2013b). It is obvious that these unlisted factors are essential in assessing the pipeline condition. However, these factors were not included in the distributed survey as their relative information were not available in the actual data of pipelines collected to validate the model as will be discussed later. It is worth to mention that the validation data was obtained before carrying this type of survey.

Phase (2): Factors' Weights and Effect Values

After identifying the factors affecting water pipelines condition, a structured questionnaire was designed and distributed among experts in the field of water pipelines and distribution networks. The questionnaires were distributed to a wide range of water network operators and professionals from different sectors, specifically, material specification engineers, water project design engineers, maintenance engineers, water system analysis engineers, water planning engineers, as well as water project consultants. Out of the 40 questionnaires distributed, a total of 23 questionnaires were collected, which represents a 57.5% response rate. The questionnaires were used to determine the importance and effect values of each factor on water pipeline conditions.

Factors' Weights

A pairwise comparison between the selected factors was performed to determine their importance effect. The pairwise comparison was conducted on three levels: (1) between the main factors with respect to the water pipeline condition; (2) between the sub-factors within each main factor; and

(3) between the main-factors with respect to each other. It is worth noting that the third level creates an inner interdependency. The pair-wise comparison for each level was designed in such a way that each respondent decides based on his/her own experience the degree of importance of each factor (X) or (Y) over the other(s) with respect to the goal under consideration. The degree of importance was scaled according to Saaty's scale (1996) from 1 to 9. An assigned value of "1" indicates that there is no significant importance of a factor over the other. On the other hand, a value of "9" indicates that there is an absolute importance for a factor over the other. For example, let us consider "level two" comparison, as shown in Table 2a. The extreme left and right columns of the table shows the factors being compared to each other. The middle column indicates that there is no domination of a factor over the other with respect to "environmental factors" when assessing the pipeline condition. Moving towards the columns on the left side of the middle column is an indication that the factor on the left side has more effect on the pipeline condition than the factor on the right side and vice versa. If we assume that the respondent affirms that the "ground water level" has a very strong importance over the "surface type" with respect to "environmental factors", then he/she should just check the appropriate box that shows such comparison. In other words, we can say that the "ground water level" factor is seven times more important than the "surface type" factor in pipeline condition assessment. The same comparison method is repeated between the "soil type" and the "surface type" factors. In this case, as shown in Table 2a, the respondent considers that both of these factors have equal effect on the pipeline condition. It is worth noting that one more comparison is not listed in the table; i.e., "ground water level" with "soil type". This comparison is determined rationally using the comparisons already made between the "surface type" and the "ground water level" as well as between the "surface type" and "soil type" as shown in Table 2a. In other words, since both "soil type" and "surface type" have equal

importance and simultaneously the “ground water level” is seven times more important than the “surface type”, then we can say that the “ground water level” is also seven times more important than the “soil type”.

Factors’ Effect Values

Each sub-factor can have several characteristics with different effects on water pipelines condition. For example, the “water quality” sub-factor has characteristics that can vary in value from 0% to 100%. These different characteristics do not have the same effect on the pipeline condition. Therefore, in this part of the questionnaire, the expert was requested to assign the effect value for each possible sub-factor characteristic using a scale from 0 to 10 to identify the worst and best effects on the pipeline condition, respectively. A sample for this part of questionnaire is shown in Table 2b. For example let us consider the “breakage rate” factor shown in Table 2b. The respondent considers that if only the “breakage rate” factor is taken into account while assessing the pipeline condition, then having high, medium, and low breakage rates will result in pipeline conditions close to 0, 6, and 10, respectively.

MODEL IMPLEMENTATION

Factors’ Weight (W_i) Determination

The FANP computational steps were followed to determine the final weights of the assessment factors using the data collected from questionnaires. The implementation of the FANP process, for each of the 23 responses received, is briefly described using the following steps:

Step 1: The elements of each level of network hierarchy are rated using the pair-wise comparison according to Saaty's scale of measurement mentioned earlier. After all elements are compared with the priority scale pair by pair, a paired comparison matrix is developed.

Step 2: Using Saaty's fuzzifying scale for the developed paired comparison matrix, lower, most probable, and upper matrices are created for all the gathered responses. Table 3 shows an example of such matrices.

Step 3: A Matlab Code is written to use the lower, most probable, and upper matrices as inputs and defuzzified to calculate the main and sub-factors' relative weights.

Step 4: The obtained defuzzified relative weights are used to build the "unweighted supermatrix".

Step 5: The "weighted supermatrix" is obtained by normalizing each column in the "unweighted supermatrix" with respect to its summation.

Step 6: The "limited supermatrix" can be calculated from the "weighted supermatrix" by raising it to large powers until the resulted matrix is equal to the previous raised matrix (Adams 2001).

Step 7: The final weights for the sub-factors using the FANP method can be obtained directly from the "limited supermatrix".

Probability Distribution Fitting

FANP was used to determine the factor final weights. Twenty three different weights were obtained for each factor based on the number of received responses. As a result, the probability distribution of the final weight of each factor was fitted. Several methods can be used to estimate probabilities that are likely to fit the collected data, such as maximum likelihood estimation, Bayesian inference, and method of moments. The software "BestFit" from Palisade Corporation

is used to fit these distributions. The software uses the maximum likelihood estimation method to perform the fitting process. Then, it ranks the fitted distribution based on three goodness-of-fit tests: (1) Kolomogorov-Smirnov (K-S); (2) Anderson-Darling (A-D); and (iii) Chi-square (Chi-sq). These tests are used to check if the data is the result of sampling a fully specified probability distribution and to estimate the values of its parameters. Table 4 shows the mean final weight of each factor that are based on the 23 responses received. The table shows that the “physical factors” possess the highest portion of effect on the pipeline condition with a 38.2%, reflecting how the respondents were keen to maintain the structural safety of the pipelines. In other words, physical factors like the pipe size, material type, and installation quality are major indicators of the pipeline condition. Small pipe sizes are more vulnerable to failure than bigger ones. Or PVC pipes are more durable than asbestos cement pipes. On the other hand, the “operational factors” resulted in the lowest portion of effect on the pipeline condition with a 28.1%. However, this does not underestimate their effect, especially when we talk about “breakage rates”. Considering all the factors individually, it can be noticed that the “ground water level” and “soil type” factors have the highest effect on the pipeline condition with a 13.7% and 13.0%, respectively. This is an indication of how the respondents emphasized on the importance of factors related to pipeline corrosion which highly affect the pipelines’ durability. Table 4 also summarizes the statistical information for the final weight distributions selected for each factor. As an example, Table 5 shows the test values for K-S, A-D, and Chi-sq as well as the critical values for the “age” factor weights at a significance level α equal to 0.01, 0.05, 0.1, and 0.25. Based upon K-S, A-D, and Chi-sq statistics, the lognormal probability distribution cannot be rejected as the best fit for the available “age” factor weights for significance levels of 1%, 5%, 10% and 25%. For example, as shown in Table 5, the critical value of the “age” factor using the K-S, A-D, and Chi-sq at a 5%

significance level is 0.913, 1.647, and 17.556, respectively. However, the test values using the K-S, A-D, and Chi-sq are 0.112, 0.365, and 2.435, respectively. Because the critical values are higher than the test values for all methods, a null hypothesis (H_0), in which the best probability fit is lognormal distribution, is accepted.

The same procedure was applied with the rest of the factors' weights as well as for the different effect values of each factor to determine the best fit probability distribution as shown in Tables 4 and 6. As a result, the two main components required to determine the overall condition index (i.e. weight and effect value) are probabilistic.

Overall Condition Index (OCI_j) Determination

Finally, the overall condition index is determined using Equation 1 for all pipelines under study simultaneously. The model simply runs by multiplying each pipeline's probabilistic effect value for each factor by the probabilistic final weight of the corresponding factor. The results of these multiplications are then added up to determine the mean overall condition index for each pipeline. This process is repeated for 1,000 iterations (simulations). The stopping criterion parameters were set equal to 5% accuracy ($\varepsilon = 0.05$) with 99% confidence. It shows the robustness of Monte-Carlo simulation algorithm where in each iteration random final weight and effect values are chosen based on the probability distribution defined for each factor. This randomness ensures that uncertainty is considered. It also ensures that the mean value of the overall condition index (OCI_j) obtained throughout the iterations is the final condition value for each pipeline. Finally, based on the condition value, the operator can decide on what actions can be taken for the pipeline, which is outside the scope of this work.

MODEL VALIDATION

The model was validated using actual data from 547 existing water pipelines that was obtained from three municipalities in Canada, namely, Moncton (New Brunswick), London (Ontario), and Longueuil (Quebec). The data included the pipelines' actual condition index in addition to the factors affecting the pipeline condition identified earlier in this study. However, it was found that the "installation quality", "ground water level", and "soil type" factors' information were incomplete. Accordingly, these three factors were not considered in the validation process and the final weights of the available factors (i.e. age, material, size, surface type, C-factor, breakage rate, and water quality) were adjusted to keep the summation of weights equal to 100%. The actual condition index for each of the 547 pipelines was provided on a scale from 0 to 10 by the municipalities based on actual pipeline inspection data. A sample of the validation data is shown in Table 7. The simulation model was used to determine the mean predicted overall condition index for each pipeline. For example, based on the characteristics of pipeline no. 325 (see Table 7), the model resulted in a mean predicted overall condition index of 7.35 as shown in Fig. 2. It is worth noting that the OCI range shown in Fig. 2 in the x-axis is from 0 to 20 despite the fact that the maximum OCI defined in this study is 10. This is due to the randomness carried in the Monte Carlo simulation process. As mentioned before, there are 23 different weights and effect values for each factor from the responses received. In each trial, the Monte Carlo simulation randomly selects a weight and an effect value for each factor from the available 23 responses and compute the pipeline condition using Equation 1. Thus, it may happen that in some trials the summation of the factor weights exceed 100%, which eventually results in an OCI above 10. For that reason, the OCI mean value is selected to represent the predicted value since it is the most probable one. In other words, the mean was selected to consider all the different weights and effect values proposed

by the 23 experts to consider the uncertainty in the responses. It could be debatable that for the OCI probability distribution sample shown in Fig. 2, the mean value loses its ability to provide the best central tendency of the distribution due to its skewness. In such case, the median value could be more representable of the distribution's central tendency. Actually, the mean best represents the central tendency of the results when we have a normal distribution or a symmetric distribution. However, in this study, when the median was selected as the predicted condition for some of the pipes with a skewed OCI distribution, the results of the model validation (discussed in the next paragraph) was less promising than if we have used the mean for all the distributions of the 547 pipelines. Again, this could be due to the fact that the mean considers all the different responses.

Validating the model requires a comparison between the predicted conditions of the 547 pipelines obtained by the developed model and the pre-known actual conditions of such pipelines. Thus, the performance of the developed model was validated using mathematical diagnostics recommended in the literature (Zayed and Halpin 2005; Al-Barqawi and Zayed 2006a). Equations 2 and 3 show the average validity/invalidity percentages (i.e., AVP and AIP). The models are sound for an AIP value closer to 0.0 and not robust for an AIP value closer to 100. Similarly, the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are estimated using Equations 4 and 5, respectively. Both RMSE and MAE values varies from 0 to infinity. If the values of RMSE and MAE are close to 0, the model is sound and vice versa (Dikmen et al. 2005). The AVP shows the accuracy of the developed model in predicting pipelines' condition and is easy to interpret by users. However, accuracy alone is not a sufficient indicator of the model performance. For instance, the difference between the predicted and actual condition for some of the pipelines could be say 5 or 6 condition units. If such big differences doesn't occur frequently, the AVP could still be high

leaving us unaware of such big differences. Thus, it is also essential to know the average magnitude of the prediction error, i.e. deviation of the predicted condition from the actual one. Both MAE and RMSE are good indicators of such error. Moreover, since the errors are squared before they are averaged, the RMSE gives a relatively high weight to large errors, i.e. penalizes large differences more than the MAE. This means that the RMSE is more useful when large errors are undesirable.

$$AIP = \left\{ \sum_{i=1}^n \left| 1 - \left(\frac{E_i}{C_i} \right) \right| \right\} \times \frac{100}{n} \quad (2)$$

$$AVP = 100 - AIP \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (C_i - E_i)^2}{n}} \quad (4)$$

$$MAE = \frac{\sum_{i=1}^n |C_i - E_i|}{n} \quad (5)$$

Where: *AIP* = Average Invalidity Percent; *AVP* = Average Validity Percent; *RMSE* = Root Mean Square Error; *MAE* = Mean Absolute Error; E_i = estimated or predicted value; C_i = actual value; and n = number of events. Based on the above discussion, the developed model was validated twice; without simulation (i.e., by directly applying Equation 1) and with simulation. The FANP model alone yielded values of 91.85%, 8.15%, 0.60, and 0.44 for the parameters *AVP*, *AIP*, *RMSE*, and *MAE*, respectively. On the other hand, the “simulated” FANP model yielded the values of 93.59%, 6.41%, 0.44, and 0.35 for the parameters *AVP*, *AIP*, *RMSE*, and *MAE*, respectively. These results are a good indicator for the robust performance of the model in accurately predicting the water pipeline condition index. However, it is clear that the simulation improved the prediction accuracy from 91.85% to 93.59% because it accounted for uncertainties.

The “actual versus predicted output plot” results for the developed model - whether simulated or non-simulated - are shown in Fig. 3. The values predicted by the developed models are within the acceptable limits. In other words, the majority of the results obtained are matching with some instances of disagreement. Therefore, the validation test results are satisfactory.

SENSITIVITY ANALYSIS

As explained earlier, the FANP technique was used to calculate the final weights of all the factors according to the questionnaires’ responses received. However, the evaluator of the developed model may have different concerns regarding those weights. In addition, receiving only 23 responses out of 40 (i.e. 57.5% response rate) is considered insufficient. In other words, if more responses were received, the final weights might have been different from those obtained in this study. To overcome this limitation, a sensitivity analysis was used to examine the effect of changing these weights on the model results. For the water pipelines, the weights of the seven factors taken into consideration were changed one at a time from 0 (i.e., the factor is not considered in the assessment process) to 1 (i.e. the factor is the only one considered in the assessment process). For instance, if the mean value of the final weight of the “age” factor is changed to 0.6 instead of the original average value of 0.082, as shown in Table 4, the weight of the other factors are set equal to the total mean weight of 0.4 ($1 - 0.6 = 0.4$). As a result the mean values of these factors are to be changed proportionally according to their average mean values shown in Table 4 to sum up to 0.4. The mean weight changing procedure took place on a 10% interval (0, 0.1, 0.2, 0.3, etc.). Accordingly, the mean overall condition index was calculated for each change for all the pipelines and their average was calculated and plotted in Fig. 4.

Fig. 4 shows that all of the seven factors were sensitive to any change in their initially determined weights. However, such sensitivity levels varied from one factor to another. Both “breakage rate” and “water quality” factors were the most sensitive followed by both “material type” and “pipe size” factors. The “C-factor” and “surface type” factors were moderately sensitive and have almost equal sensitivity. Finally, the “age” factor was the least sensitive.

WATER PIPELINES CONDITION ASSESSMENT DATABASE

In order to facilitate the use of the developed simulation model, a Matlab code was written in order to generate all possible combinations with their identified factors and corresponding qualitative characteristics. As shown in Table 6, each factor has three or more possible characteristics. For example, the “size” factor has three characteristics (i.e. small, medium, and large). Permuting the characteristics of all factors generated a total possible number of combinations equal to 131,220. The developed simulation model used the generated database to determine the predicted overall condition index for each case. The database is useful to facilitate the determination of the overall condition index for a given pipeline as soon as its characteristics are known. A database sample for ductile iron pipelines is shown in Table 8. For instance, let us assume a 40-year old ductile iron water pipeline with a 150-mm diameter. Let us also assume that the pipeline needs a high installation quality and is located under asphalt with a very close ground water level. Moreover, the pipeline’s surrounding soil type is assumed to be aggressive and carries water with medium level of impurities. Finally, the pipeline C-factor and breakage rate are assumed to be equal to 120 and 0.8, respectively. Based on such assumptions and with the help of Table 6, the qualitative characteristics of this pipeline will be: medium, ductile iron, small, good, asphalt, shallow, aggressive, high, high, and fair for the factors: age, material type, size, installation quality, surface

type, ground water level, soil type, C-factor, breakage rate, and water quality, respectively. Using Table 8, the case that matches the pipeline characteristics is case number 8750 which predicts a condition index of “5.6”.

WATER PIPELINES DETERIORATION MODELS

The developed condition assessment database is used to develop different deterioration models for water pipelines based on different pre-defined factor combinations. Practically, the factors of size (SZ), material (MT), installation quality (IQ), surface type (SR), ground water level (GW), and soil type (SL) are considered constant throughout a pipeline lifetime. Thus, the factors that change with age will be the C-factor (CF), breakage rate (BR), and water quality (WQ). Fig. 5 shows integrated deterioration curves for three ductile iron pipeline sizes (i.e., small, medium, and large) based on the previous assumptions. Three curves were plotted. The first one (from installation time to year 30) was plotted assuming the best characteristic combinations for the IQ, ST, GW, and SL factors. The second curve (from years 31 to 70) was plotted assuming moderate characteristic combinations for the IQ, ST, GW, and SL factors. Finally, the third one (from years 71 to 100) was plotted assuming the worst characteristic combinations for the IQ, ST, GW, and SL factors. For the three sectors, the CF, BR, and WQ factors were changed reasonably with respect to age.

Alternatively, individual water pipeline deterioration curves or models can be also developed from the developed database by alternating the possible characteristics of the SZ, MT, IQ, SR, GW, and SL factors during the pipeline estimated lifetime. Thus, 1,620 different deterioration curves can be developed representing all possible cases while changing the CF, BR, and WQ factors reasonably throughout the pipe’s lifetime. Fig. 6 shows a sample of such deterioration curves and their

patterns. For instance, Fig. 6a shows the effect on the deterioration pattern of a water pipeline with different pipe sizes when the MT is “ductile iron”, IQ is “good”, SR is “unpaved”, GW is “moderate”, and SL is “moderate”. It is clear from the figure, that large size pipelines have better condition throughout their lifetime than smaller size ones. Usually, smaller diameter pipelines have a higher probability of failure than larger ones because smaller standard dimension ratios (SDR) may affect the structural performance of a pipeline and makes it more vulnerable to external impact or third party damage. In addition, smaller diameters have thinner wall thickness which allows for faster corrosion rate. Fig. 6b shows the effect on the deterioration pattern of a water pipeline with different pipe materials when the SZ is “medium”, IQ is “good”, SR is “unpaved”, GW is “moderate”, and SL is “moderate”. The figure shows that PVC pipes result in higher condition throughout their lifetime than other pipe materials due to their lower breakage rate and corrosion resistance. The same concept is illustrated in figures 6c through 6f for different installation qualities, surface types, ground water level, and soil type. Additional deterioration curves other than those illustrated in Fig. 6 can be plotted by changing the factors’ attributes.

From the deterioration curves shown in Fig. 6, different deterioration models can be developed as a function of the pipeline’s age. This is done by identifying a relationship between the pipeline’s condition index and its age. Thus, 16 different deterioration models can be developed for only the deterioration curves shown in Fig. 6. Table 9 shows the 16 deterioration models where X and Y represents the pipeline’s age and condition index, respectively. The statistical results (R^2 , adjusted R^2 , standard error, and p-value) shown in the table indicates that the deterioration models are sound and robust. As a result, if a municipal engineer needs to know the condition index of a “ductile iron” pipeline, he/she can select the appropriate deterioration model from Table 9. For example,

let us say that the SZ, IQ, SR, GW, and SL were medium, good, unpaved, shallow, and moderate, respectively, and the age is 60 years. As a result, the appropriate deterioration model that matches the mentioned attributes is number 13 in Table 9. Thus, substituting the age of 60 years in the model will result in a condition index of 6.4. It is worth mentioning that the deterioration curves and models shown in Figures 5 and 6 and Table 9 does not take into consideration any type of repair, rehabilitation, or maintenance actions that usually takes place.

DISCUSSIONS AND LIMITATIONS

It is difficult to develop a generalized universally applicable condition assessment and deterioration models for water pipelines. The developed models in this study tried to add flexibility in their application by incorporating different pipelines material types and sizes. However, the data collected to build up such models could vary from a place to another or even from a decision maker to another. The factors' weights obtained were based on questionnaires distributed to experts from North America. Experts from Montreal for example, may have had some bias towards assigning higher weights to the "material type" factor due to the old infrastructure system in the city. Experts from another city or country (especially developing countries) with relatively newly installed infrastructure system may have assigned a lower weight. Another example is that the "temperature fluctuation" factor could be applicable in cold regions while not applicable in hot regions such as the Middle East. On the other hand, it is difficult to have full historical database of water pipelines that incorporates the factors used in this study or even other essential factors not included in this study. For example, the "ground water level" or "soil type" factors for a full network cannot be easily obtained as it happened in this study. Despite that, the model predicted the pipelines' condition with acceptable accuracy. With that been said, the developed models in this study can

be considered as a guideline for decision makers to assess the condition and deterioration of their water infrastructure. The same methodology proposed in this study can be applied by the decision makers anywhere using their own representable factors and their corresponding weights based on their experience or new surveys.

Apart from the models' applicability, some limitations should be addressed to improve the models' capabilities. More data should be collected in order to consider the neglected factors (e.g. soil type, ground water level, temperature fluctuation, point loads, pipe lining and coating, stray current, etc.). Also, the number of responses received to determine the factors' weights can be considered relatively low. To sum up, infrastructure asset management tools are always hungry for data, the more data collected the more robust and credible tools to be developed.

CONCLUSIONS

This paper presents the development of a condition assessment model and deterioration models for water pipelines considering uncertainties and interdependencies among factors and sub-factors. A total of ten factors were identified to affect the condition of water pipelines. These factors were divided into three main categories, namely, physical, environmental, and operational. The importance weights of these factors were calculated using FANP technique which allowed the consideration of their inner interdependencies. The physical factors had the highest importance with a total weight of around 38%. This is expected since the actual physical characteristics of the pipeline contribute significantly to its overall performance. Most of the sub-factors recorded similar importance weights within the range of 10%. The “ground water level” factor was found to be the most influential factor followed by the “soil type” with a weight of 13.7% and 13.0%,

respectively. On the other hand, the least affecting factor was the “surface type” with a weight of 7.1%. An integrated simulation/FANP model was developed to assess the condition of water pipelines. This integration provides three main benefits: (1) making decisions under uncertainty, (2) encompassing interdependencies among criteria, and (3) handling decisions that involve large number of variables. The model was validated using the data of 547 existing water pipelines in Canada. The validation results showed that taking simulation into consideration improved the prediction accuracy from 91.85% to 93.59% as it accounts for uncertainties. Such accuracy indicates a satisfactory model performance. A sensitivity analysis was carried to examine the effect of changing the factors’ weight of importance. It was found that all factors were sensitive - with varying levels - to any change that could happen, which shows that the final evaluator should be careful in assigning his/her own weights. The developed condition assessment model was used to develop a database containing a total of 131,220 different cases that were generated by considering all possible factors’ characteristics combinations and their corresponding predicted conditions. The database was used to develop different deterioration curves and models to identify deterioration patterns of water pipelines with respect to different sizes and materials as well as different surrounding environmental conditions. The models are expected to help municipalities and decision makers to accurately plan for future water pipelines maintenance and rehabilitation activities. The planning depends on the pipeline current condition considering the uncertainties at initial stages and those accumulated during the calculation process.

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Table 1: Factors Affecting Water Pipelines Condition

Main Factors	Sub-Factors	Description
PHYSICAL (P)	Age (AG)	Effects of pipeline degradation become more significant over time.
	Material (MT)	Different pipeline material types are associated with different failure modes.
	Size (SZ)	Pipeline size includes diameter, thickness, and length. The smaller is the pipeline diameter, the higher is its deterioration rate. The larger is the thickness, the higher is the corrosion resistance. The longer is the pipeline, the higher is the deterioration rates and vice versa.
	Installation Quality (IQ)	Measure whether or not the installation was done as per specifications and standards. Poor installation quality leads to a higher breakage rate; improper pipe bedding may result in pipe failure.
ENVIRONMENTAL (E)	Surface Type/Location (SR)	Pipeline location is related to the installation zone being residential, industrial, school, etc. Pipelines in residential areas are exposed to different conditions than those located in industrial areas or cities because they may be located under different surface types (e.g. asphalt, seal, unpaved etc.). City pipelines are subject to heavy traffic adding more dynamic load on the pipeline.
	Ground Water Level (GW)	This factor refers to the degree to which groundwater affects the pipe. The amount of water in soil affects the soil resistivity, which inversely relates to the corrosion rate. The ground water may lead to corroding the pipe directly when salts and some corrosive substances exist in it.
	Soil Type (SL)	This factor refers to the type of soil in direct contact with the pipe surface. Different soils have different impacts on the pipeline. Some soils are corrosive; others experience significant volume changes in response to moisture changes, resulting in changes to pipe loading. Presence of hydrocarbons and solvents in soil may cause pipe deterioration.
OPERATIONAL (O)	Hazen-Williams Coefficient (CF)	The pressure resulting from transients in the water distribution system may cause pump and device failure, system fatigue, or pipe ruptures. High velocity water corrodes the internal walls of the pipe and causes disturbances especially when moving between pipes of different diameters. Both pressure and flow velocity contributes to Hazen-Williams coefficient (C-Factor). A low C-Factor indicates a low pipeline condition and vice versa.
	Leakage/ Breakage rate (BR)	Leakage relates to water penetration from the pipe through surface cracks. The leaked water widens cracks, increases the surrounding soil moisture content and the probability of external corrosion. This may cause changes in the stress distribution on the pipe and eventually leads to pipe breakage. Breakage rate is the number of breaks/km/year. High breakage rate indicates a poor condition pipeline and thus requires rehabilitation actions.
	Water Quality (WQ)	Chemicals and substances (such as salts and micro-bio species) present in water while being transported decrease water quality. They can also corrode the internal surface of the pipe and cause its breakage.

Table 2: Questionnaire Form Sample

(a) Factors' Pairwise Comparison

Factor (X)	Degree of Importance								Factor (Y)	
	(9) Absolute	(7) Very Strong	(5) Strong	(3) Moderate	(1) Equal	(3) Moderate	(5) Strong	(7) Very Strong		(9) Absolute
ENVIRONMENTAL FACTORS										
Surface Type								✓		Ground Water Level
					✓					Soil Type

(b) Factor Effect Values

Main Factor	Sub-factor	Characteristics	Effect Value on Pipeline Condition (0 – 10)
OPERATIONAL	Hazen-Williams Coefficient (C-factor)	Low (< 41)	2
		Medium (41 - 101)	7
		High (> 101)	10
	Leakage/Breakage Rate (breaks/km/year)	High (> 0.5)	0
		Medium (0.1 – 0.5)	6
		Low (< 0.1)	10
	Water Quality	Poor	3
		Fair	5
		Good	10

Table 3: Lowest, Most Probable, and Upper Limit Matrices Sample

FACTORS	Lower Limit Matrix			Most Probable Matrix			Upper Limit Matrix		
	Surface Type	Ground Water Level	Soil Type	Surface Type	Ground Water Level	Soil Type	Surface Type	Ground Water Level	Soil Type
Surface Type	1	1/8	1	1	1/7	1	1	1/6	1
Ground Water Level	6	1	6	7	1	7	8	1	8
Soil Type	1	1/8	1	1	1/7	1	1	1/6	1

Table 4: Summary of Statistical Analysis Results for Factor Weights

Main Factor	Sub-Factor	Distribution	Mean Final Weight (μ)	Standard Deviation (σ)	Variance (σ^2)	Standard Error (ε)	Test Values		
							A-D Test	K-S Test	Chi-Sq Test
PHYSICAL	AG	Lognormal	0.082	0.08	0.010	0.02	0.365	0.112	2.435
	MT	Exponential	0.095	0.06	0.002	0.01	1.053	0.157	2.435
	SZ	Exponential	0.096	0.09	0.010	0.02	0.623	0.144	3.304
	IQ	Min.Extreme	0.109	0.07	0.010	0.01	0.677	0.172	4.174
ENVIRONMENTAL	SR	Lognormal	0.071	0.09	0.010	0.02	0.279	0.111	2.000
	GW	Gamma	0.137	0.08	0.010	0.02	0.176	0.083	2.000
	SL	Exponential	0.130	0.10	0.010	0.02	0.327	0.106	1.130
OPERATIONAL	CF	Exponential	0.081	0.09	0.010	0.02	0.224	0.093	1.130
	BR	Lognormal	0.098	0.09	0.010	0.02	0.281	0.104	0.696
	WQ	Lognormal	0.102	0.07	0.010	0.01	0.355	0.097	1.130

Table 5: Hypothesis Testing for the “Age” Factor’s Weight

PARAMETER	A-D Test	K-S Test	Chi-Sq Test
Distribution	Lognormal	Lognormal	Lognormal
Test Value	0.365	0.112	2.435
Critical Value at $\alpha = 0.25$	0.589	0.546	11.861
Critical Value at $\alpha = 0.10$	1.025	0.789	14.743
Critical Value at $\alpha = 0.05$	1.647	0.913	17.556
Critical Value at $\alpha = 0.01$	2.919	1.266	21.008
Reject H_0?	No	No	No

Table 6: Summary of Statistical Analysis Results for Factor Effect Values

Factor	Characteristics	Distribution	Mean Effect Value (μ)	Standard Deviation (σ)	Variance (σ^2)	Standard Error (ϵ)	Test Values		
							A-D Test	K-S Test	Chi-Sq Test
AG	Old (> 70 years)	Normal	1.24	1.300	1.690	0.28	1.149	0.239	2.429
	Medium (30 – 70 years)	Uniform	4.81	1.401	1.962	0.01	1.108	0.218	1.286
	New (< 30 years)	Max. Extreme	9.52	0.602	0.362	0.13	2.497	0.312	18.809
MT	Asbestos	Normal	5.52	0.981	0.962	0.21	1.127	0.218	6.238
	Cast Iron	Uniform	5.62	0.921	0.848	0.20	1.456	0.272	6.238
	Concrete	Max. Extreme	6.62	0.865	0.748	0.19	1.517	0.234	10.809
	Ductile Iron	Uniform	7.62	1.024	1.048	0.22	2.659	0.313	10.429
	PVC	Lognormal	9.52	0.750	0.562	0.16	2.963	0.347	20.714
SZ	Small (< 200 mm)	Gamma	3.10	1.546	2.390	0.34	0.857	0.193	8.143
	Medium (200 – 350 mm)	Normal	6.48	1.365	1.862	0.30	1.204	0.201	2.429
	Large (> 350 mm)	Max. Extreme	9.67	0.658	0.433	0.14	4.110	0.417	32.524
IQ	Poor	Normal	2.52	1.692	2.862	0.37	0.419	0.151	0.524
	Fair	Uniform	5.81	1.504	2.262	0.33	0.951	0.218	1.286
	Good	Max. Extreme	9.52	0.750	0.562	0.16	3.184	0.371	21.095
SR	Asphalt	Uniform	4.57	2.619	6.857	0.47	1.280	0.214	3.952
	Seal	Normal	6.29	2.493	6.214	0.44	0.426	0.135	6.619
	Foot Path	Normal	7.24	2.211	4.890	0.48	0.579	0.159	0.143
	Unpaved	Normal	7.57	2.293	5.257	0.50	0.773	0.189	1.667
GW	Shallow	Max. Extreme	2.24	1.814	3.290	0.40	0.812	0.196	3.952
	Moderate	Uniform	5.67	1.528	2.333	0.33	0.739	0.218	2.429
	Deep	Beta	9.57	0.598	0.357	0.13	2.6537	0.3243	23.381
SL	Aggressive	Logistic	1.67	1.826	3.333	0.30	1.042	0.203	2.429
	Moderate	Gamma	5.00	1.304	1.700	0.28	0.931	0.220	8.524
	Non-Aggressive	Max. Extreme	9.86	0.359	0.129	0.08	5.694	0.483	42.428
CF	Low (< 41)	Pareto	3.43	1.469	2.157	0.32	3.296	0.376	3.571
	Medium (41 – 101)	Uniform	6.24	1.578	2.490	0.34	1.204	0.300	10.048
	High (> 101)	Max. Extreme	9.90	0.301	0.090	0.07	6.366	0.495	48.524
BR	High (> 0.5 breaks/km/yr)	Logistic	1.62	1.465	2.148	0.32	0.837	0.168	1.286
	Medium (0.1 – 0.5 breaks/km/yr)	Normal	4.62	1.322	1.748	0.29	0.712	0.196	2.048
	Low (< 0.1 breaks/km/yr)	Max. Extreme	9.95	0.218	0.048	0.05	7.136	0.497	55.381
WQ	Poor (High Impurities Level)	Normal	2.10	1.578	2.490	0.34	0.503	0.143	2.048
	Fair (Medium Impurities Level)	Normal	5.14	1.315	1.729	0.29	0.858	0.219	3.952
	Good (Low Impurities Level)	Max. Extreme	9.90	0.301	0.090	0.07	6.366	0.495	48.524

Table 7: Sample of Validation Data

PIPELINE #	AGE (Years)	MATERIAL TYPE	SIZE (mm)	SURFACE TYPE	C- FACTOR	BREAKGAE RATE (breaks/km/year)	WATER QUALITY	ACTUAL CONDITION INDEX
51	48	Cast Iron	150	Asphalt	73	0.4	Good	6.2
52	26	Ductile Iron	200	Asphalt	95	0.2	Poor	4.6
53	47	Cast Iron	150	Asphalt	74	0.0	Good	8.6
113	56	Cast Iron	150	Asphalt	65	5.0	Good	4.6
114	10	PVC	150	Asphalt	111	0.3	Poor	5.0
162	47	Asbestos	300	Asphalt	74	0.1	Poor	5.2
193	56	Cast Iron	150	Asphalt	65	0.0	Good	8.6
227	33	Ductile Iron	150	Asphalt	88	1.3	Poor	3.4
228	33	Ductile Iron	150	Asphalt	88	0.9	Poor	3.8
229	30	Ductile Iron	150	Asphalt	91	0.3	Poor	4.6
274	61	Cast Iron	150	Asphalt	60	0.0	Good	8.2
275	47	Asbestos	150	Asphalt	74	0.3	Poor	4.2
276	53	Cast Iron	300	Asphalt	68	0.5	Good	6.4
324	46	Cast Iron	200	Asphalt	75	0.7	Good	5.4
325	48	Cast Iron	200	Asphalt	73	0.2	Good	7.0
326	22	Ductile Iron	200	Asphalt	99	0.5	Poor	3.8
377	49	Cast Iron	150	Asphalt	72	0.8	Good	5.4
418	41	Cast Iron	200	Asphalt	80	0.4	Good	6.2
419	36	Cast Iron	150	Asphalt	85	0.2	Good	7.4
528	38	Cast Iron	200	Asphalt	83	0.2	Good	6.6

Table 8: Sample of Condition Assessment Database

Case #	Age	Material Type	Size	Installation Quality	Surface Type	Ground Water Level	Soil Type	C-Factor	Breakage Rate	Water Quality	Condition Index
55	Old	Ductile Iron	Small	Good	Foot Path	Shallow	Aggressive	High	High	Poor	5.1
56	Old	Ductile Iron	Small	Good	Foot Path	Shallow	Aggressive	High	High	Fair	5.4
4333	Old	Ductile Iron	Medium	Fair	Asphalt	Moderate	Moderate	Medium	Medium	Poor	5.2
4334	Old	Ductile Iron	Medium	Fair	Asphalt	Moderate	Moderate	Medium	Medium	Fair	5.5
4335	Old	Ductile Iron	Medium	Fair	Asphalt	Moderate	Moderate	Medium	Medium	Good	6.0
8693	Old	Ductile Iron	Large	Poor	Seal	Deep	Non-Aggressive	Low	Low	Fair	6.9
8694	Old	Ductile Iron	Large	Poor	Seal	Deep	Non-Aggressive	Low	Low	Good	7.4
8749	Medium	Ductile Iron	Small	Good	Asphalt	Shallow	Aggressive	High	High	Poor	5.3
8750	Medium	Ductile Iron	Small	Good	Asphalt	Shallow	Aggressive	High	High	Fair	5.6
13135	Medium	Ductile Iron	Medium	Fair	Foot Path	Moderate	Moderate	Medium	Medium	Poor	5.7
13136	Medium	Ductile Iron	Medium	Fair	Foot Path	Moderate	Moderate	Medium	Medium	Fair	6.0
13137	Medium	Ductile Iron	Medium	Fair	Foot Path	Moderate	Moderate	Medium	Medium	Good	6.5
17441	Medium	Ductile Iron	Large	Poor	Seal	Deep	Non-Aggressive	Low	Low	Fair	7.3
17442	Medium	Ductile Iron	Large	Poor	Seal	Deep	Non-Aggressive	Low	Low	Good	7.7
17497	New	Ductile Iron	Small	Good	Asphalt	Shallow	Aggressive	High	High	Poor	5.8
17498	New	Ductile Iron	Small	Good	Asphalt	Shallow	Aggressive	High	High	Fair	6.0
21883	New	Ductile Iron	Medium	Fair	Foot Path	Moderate	Moderate	Medium	Medium	Poor	6.2
21884	New	Ductile Iron	Medium	Fair	Foot Path	Moderate	Moderate	Medium	Medium	Fair	6.5
21885	New	Ductile Iron	Medium	Fair	Foot Path	Moderate	Moderate	Medium	Medium	Good	6.9
26189	New	Ductile Iron	Large	Poor	Seal	Deep	Non-Aggressive	Low	Low	Fair	7.7
26190	New	Ductile Iron	Large	Poor	Seal	Deep	Non-Aggressive	Low	Low	Good	8.2

Table 9: Deterioration Models Sample

Model #	PIPE CHARACTERISTICS						MODEL	R Square	Adjusted R Square	Standard Error	P-Value
	SZ	MT	IQ	SR	GW	SL					
1	Small	Ductile Iron	Good	Unpaved	Moderate	Moderate	$Y = -1E-5x^3 + 0.0020x^2 - 0.1434x + 9.9748$	0.9213	0.9203	0.2354	7.9E-7
2	Medium	Ductile Iron	Good	Unpaved	Moderate	Moderate	$Y = -1E-5x^3 + 0.0018x^2 - 0.1312x + 10.032$	0.9288	0.9279	0.2217	1.3E-7
3	Large	Ductile Iron	Good	Unpaved	Moderate	Moderate	$Y = -9E-6x^3 + 0.0017x^2 - 0.1225x + 10.075$	0.9426	0.9418	0.1955	2.6E-8
4	Medium	Asbestos	Good	Unpaved	Moderate	Moderate	$Y = -1E-5x^3 + 0.0021x^2 - 0.1480x + 9.9528$	0.9161	0.9150	0.2447	5.9E-6
5	Medium	Cast Iron	Good	Unpaved	Moderate	Moderate	$Y = -1E-5x^3 + 0.0020x^2 - 0.1422x + 9.9805$	0.9226	0.9217	0.2331	5.7E-7
6	Medium	Concrete	Good	Unpaved	Moderate	Moderate	$Y = -1E-5x^3 + 0.0019x^2 - 0.1365x + 10.008$	0.9276	0.9254	0.2261	3.5E-7
7	Medium	PVC	Good	Unpaved	Moderate	Moderate	$Y = -9E-6x^3 + 0.0017x^2 - 0.1249x + 10.063$	0.9404	0.9396	0.1998	2.8E-8
8	Medium	Ductile Iron	Poor	Unpaved	Moderate	Moderate	$Y = -1E-5x^3 + 0.0027x^2 - 0.1835x + 9.7831$	0.8717	0.8701	0.3194	3.8E-4
9	Medium	Ductile Iron	Fair	Unpaved	Moderate	Moderate	$Y = -1E-5x^3 + 0.0023x^2 - 0.1600x + 9.8956$	0.9019	0.9007	0.2693	4.0E-5
10	Medium	Ductile Iron	Good	Asphalt	Moderate	Moderate	$Y = -1E-5x^3 + 0.0022x^2 - 0.1562x + 9.9139$	0.9066	0.9054	0.2614	1.8E-5
11	Medium	Ductile Iron	Good	Seal	Moderate	Moderate	$Y = -1E-5x^3 + 0.0021x^2 - 0.1469x + 9.9581$	0.9174	0.9164	0.2425	1.9E-6
12	Medium	Ductile Iron	Good	Foot Path	Moderate	Moderate	$Y = -1E-5x^3 + 0.0020x^2 - 0.1413x + 9.9849$	0.9237	0.9227	0.2312	4.4E-7
13	Medium	Ductile Iron	Good	Unpaved	Shallow	Moderate	$Y = -1E-5x^3 + 0.0021x^2 - 0.1494x + 9.9464$	0.9146	0.9135	0.2474	7.1E-6
14	Medium	Ductile Iron	Good	Unpaved	Deep	Moderate	$Y = -8E-6x^3 + 0.0015x^2 - 0.1149x + 10.111$	0.9492	0.9486	0.1820	2.2E-8
15	Medium	Ductile Iron	Good	Unpaved	Moderate	Aggressive	$Y = -1E-5x^3 + 0.0021x^2 - 0.1496x + 9.9453$	0.9143	0.9133	0.2479	7.3E-6
16	Medium	Ductile Iron	Good	Unpaved	Moderate	Non-Aggressive	$Y = -8E-6x^3 + 0.0015x^2 - 0.1145x + 10.113$	0.9495	0.9489	0.1814	1.5E-8

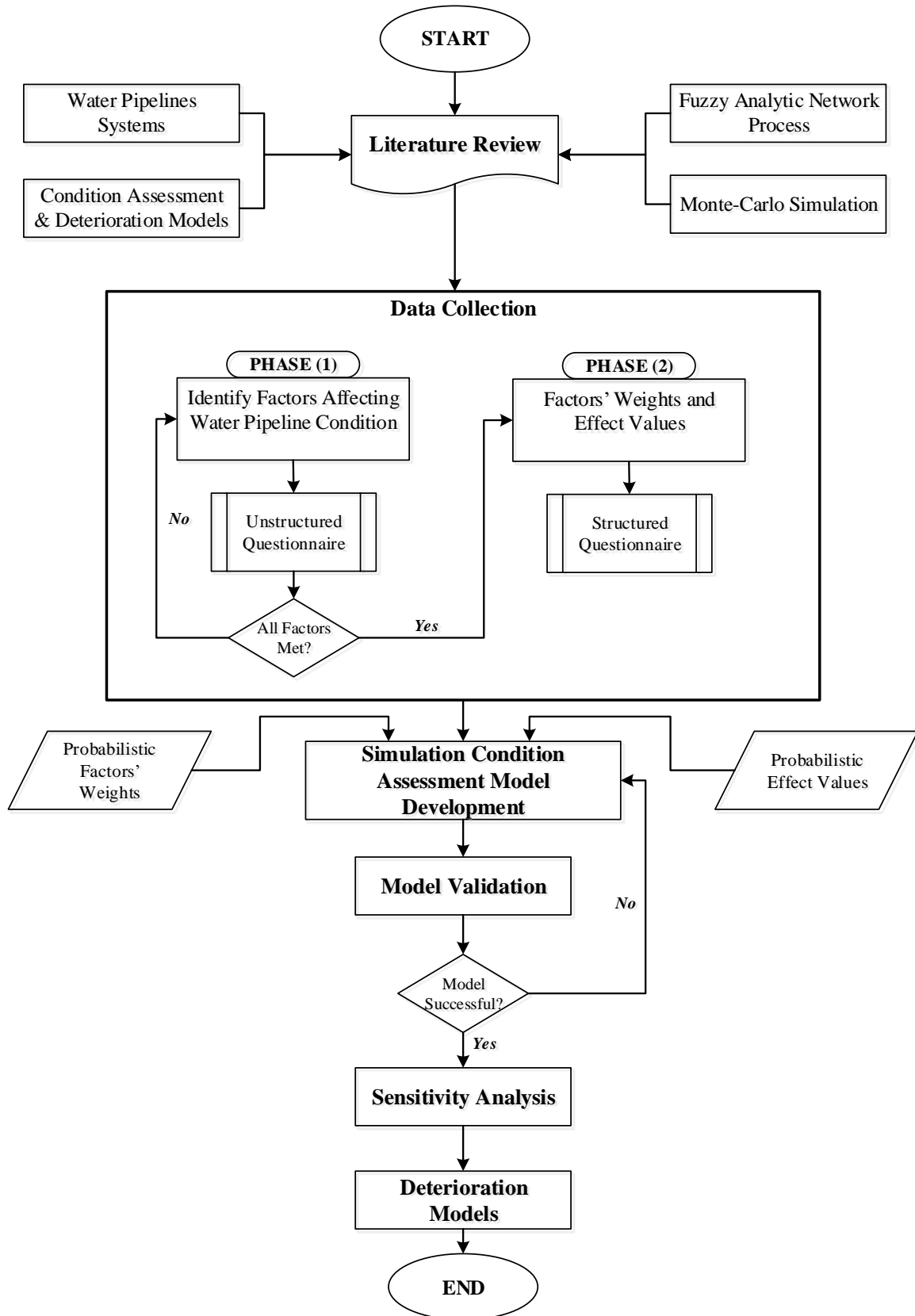


Fig. 1: Research Methodology

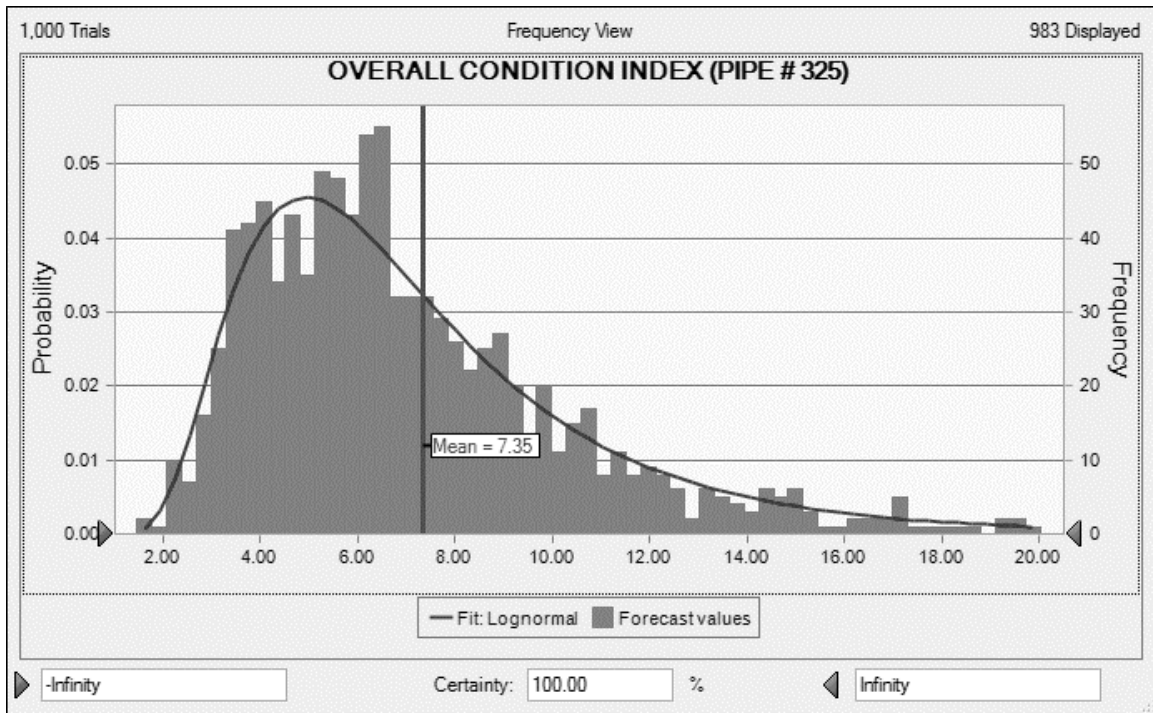


Fig. 2: Overall Condition Index Probability Distribution for Pipeline No. 325

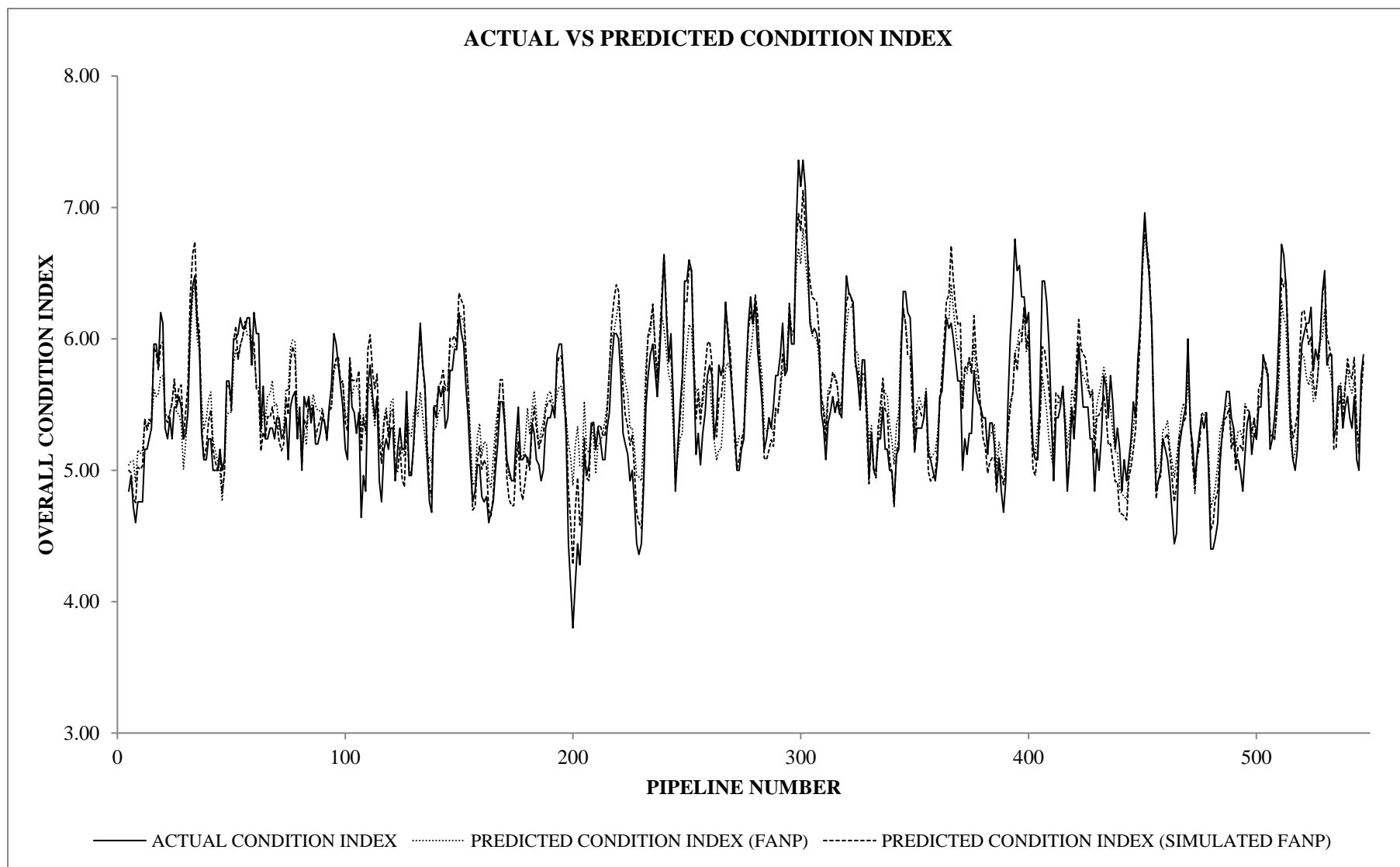


Fig. 3: Model Validation Plot

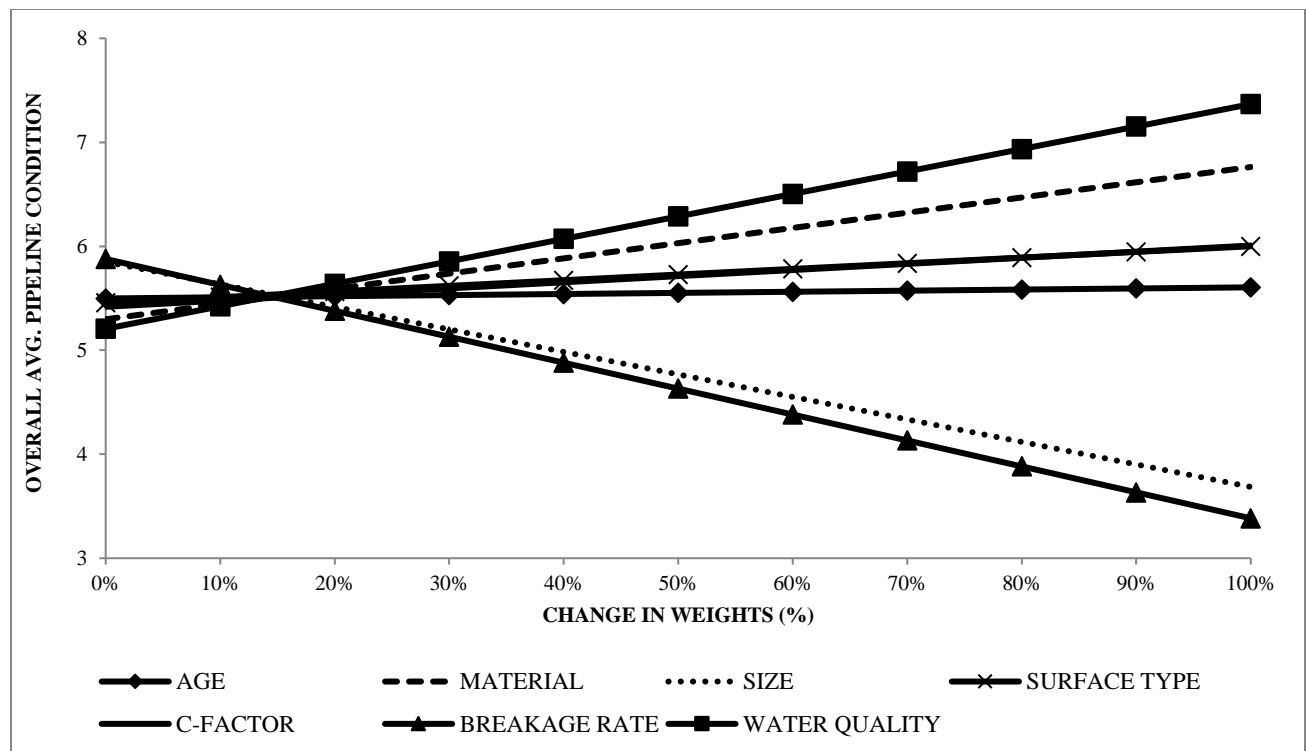


Fig. 4: Sensitivity Analysis

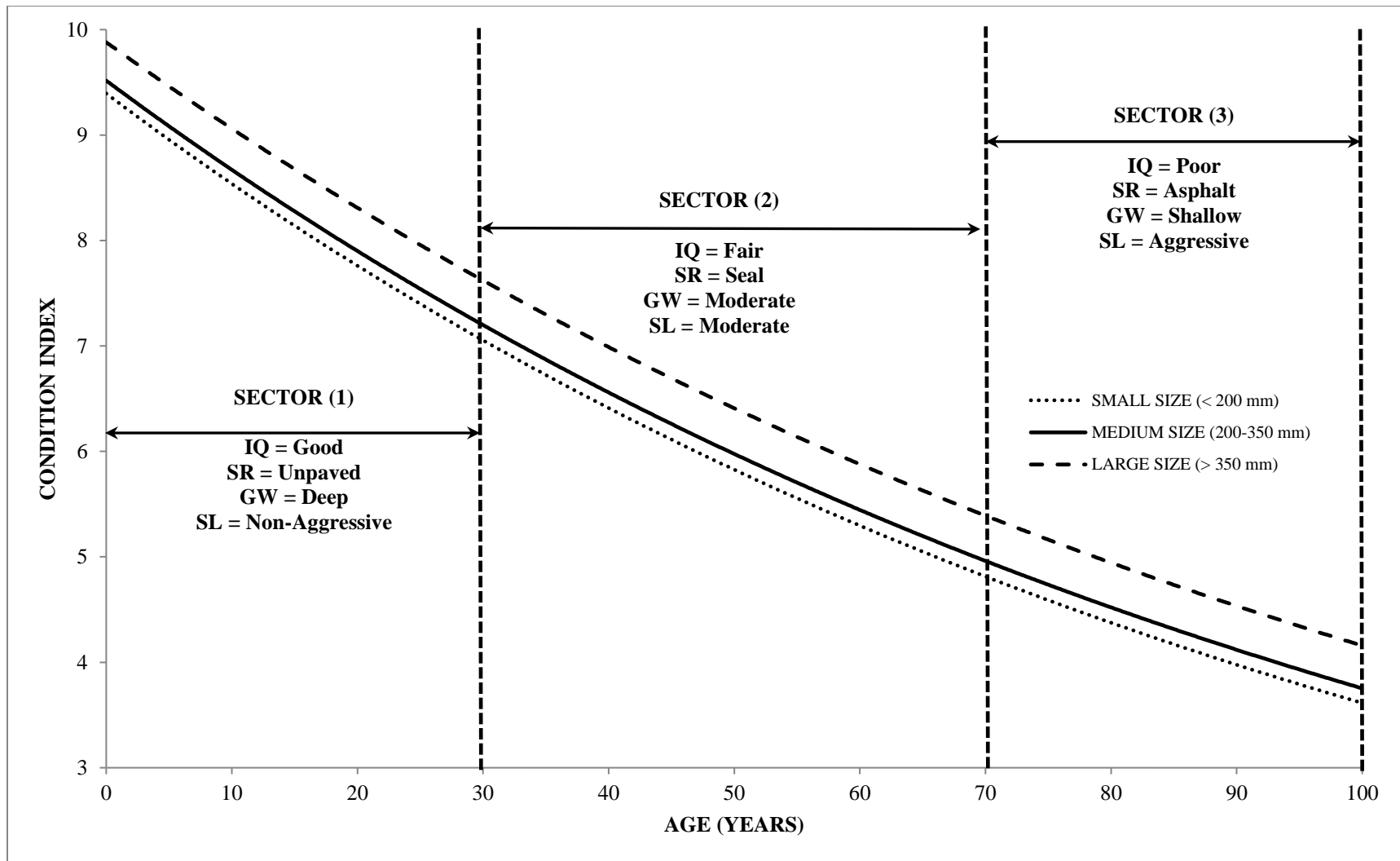


Fig. 5: Integrated Deterioration Curves

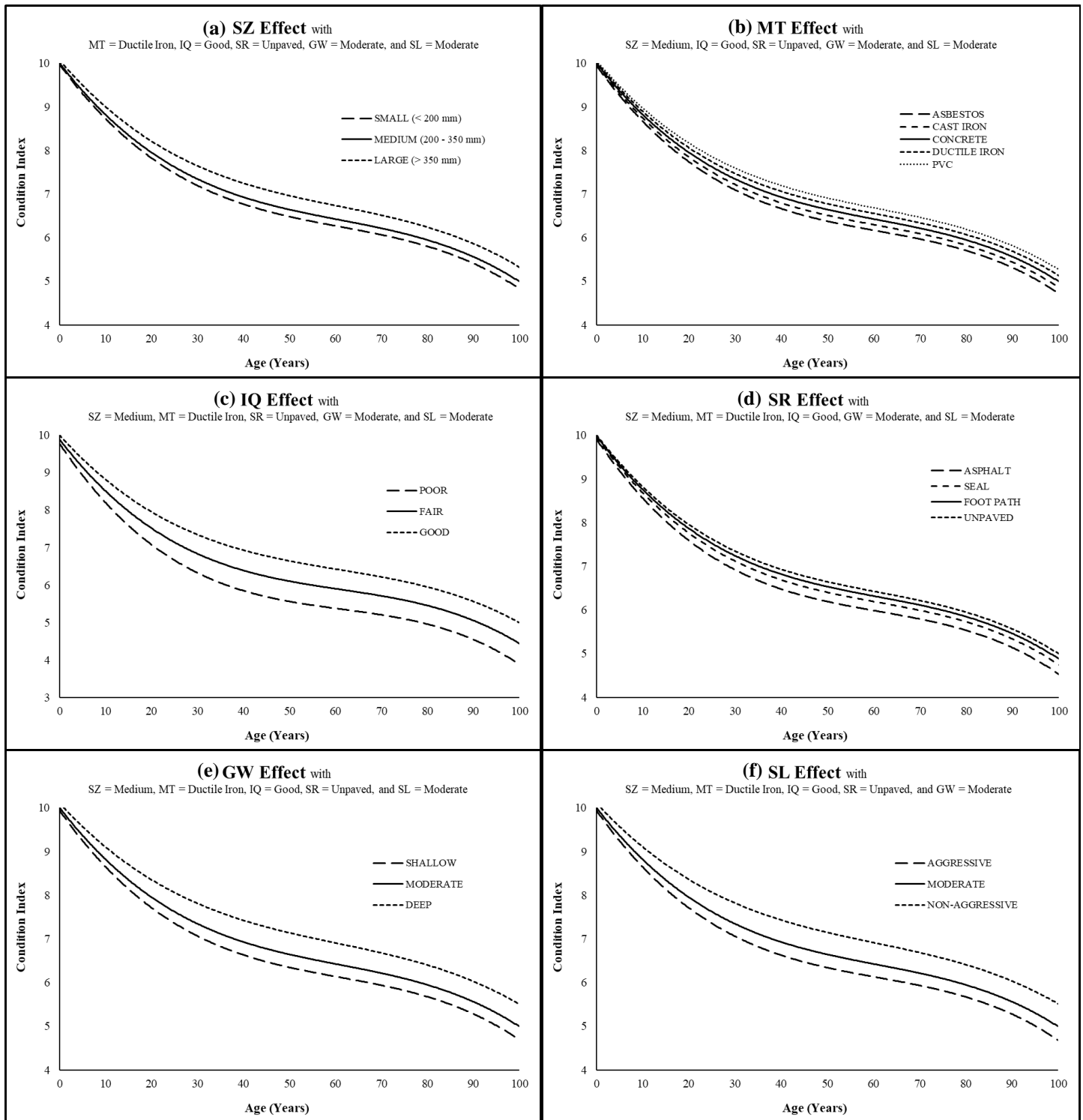


Fig. 6: Deterioration Curves Sample