QATAR UNIVERSITY

COLLEGE OF ENGIEERING

CONDITION ASSESSMENT MODELS FOR SEWER PIPELINES

BY

FIRAS AMER ABDULRAZAK ALKADOUR

A Thesis Submitted to the Faculty of

the College of Engineering

In Partial Fulfillment

of the Requirements

for the Degree of

Master of Science in

Civil Engineering

June 2017

© 2017 Firas Amer Abdulrazak Alkadour. All Rights Reserved

COMMITTEE PAGE

The members of the Committee approve the thesis of Firas Alkadour defended on 18-05-2017

Dr. Alaa Al-Hawari
Thesis/Dissertation Supervisor

Dr. Murat Gunduz
Chair

Dr. Mohsin Siddiqui
Committee Member

Dr. Hesham Osman
Committee Member

Approved:

Khalifa Al-Khalifa, Dean, College of Engineering

Abstract

ABDULRAZAK ALKADOUR, FIRAS, AMER., Masters : June : 2017,

Masters of Science in Civil Engineering

Title: Condition Assessment Models for Sewer Pipelines

Supervisor of Thesis: Dr. Alaa Al-Hawari.

Underground pipeline system is a complex infrastructure system that has significant impact on social, environmental and economic aspects. Sewer pipeline networks are considered to be an extremely expensive asset. This study aims to develop condition assessment models for sewer pipeline networks. Seventeen factors affecting the condition of sewer network were considered for gravity pipelines in addition to the operating pressure for pressurized pipelines. Two different methodologies were adopted for models' development. The first method by using an integrated Fuzzy Analytic Network Process (FANP) and Monte-Carlo simulation and the second method by using FANP, fuzzy set theory (FST) and Evidential Reasoning (ER). The models' output is the assessed pipeline condition. In order to collect the necessary data for developing the models, questionnaires were distributed among experts in sewer pipelines in the state of Qatar. In addition, actual data for an existing sewage network in the state of Qatar was used to validate the models' outputs. The "Ground Disturbance" factor was found to be the most influential factor followed by the "Location" factor with a weight of 10.6% and 9.3% for pipelines under gravity and 8.8% and 8.6% for pipelines under pressure, respectively. On the other hand, the least affecting factor was the "Length" followed by "Diameter" with weights of 2.2% and 2.5% for pipelines under gravity and 2.5% and 2.6% for pipelines under pressure.

The developed models were able to satisfactorily assess the conditions of deteriorating sewer pipelines with an average validity of approximately 85% for the first approach and 86% for the second approach. The developed models are expected to be a useful tool for decision makers to properly plan for their inspections and provide effective rehabilitation of sewer networks.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

The Thesis has been prepared under the direct supervision of Dr. Alaa AlHawari, Professor of Civil Engineering, to whom the writer is indebted for his guidance, constructive criticism, and encouragement in the preparation of the manuscript. This research was made possible by NPRP grant # (NPRP6-357-2-150) from the Qatar National Research Fund (Member of Qatar Foundation).

Also, the writer would like to thank Dr. Tarek Zayed, Professor of Civil Engineering at Concordia University for his support in the analysis part, the Public Works Authority of Qatar (ASHGAL) for their support in the data collection.

The writer gratefully appreciates the continued support and patience of his parents and family throughout his education.

CHAPTER 1- INTRODUCTION

1.1 Overview

The condition and level of service of sewage pipelines could have major effect on environmental and economic aspects for populated urban areas. Deteriorated sewage pipelines are considered hazardous on the public healthiness and environment. The performance of sewage pipelines is a function in reliability, and level of service by which decision makers can determine the lifecycle of the pipeline and the time for interventions required to reinstate the level of service of deteriorated pipes back to the desired level. Maintenance, rehabilitation and renewal comprises the intervention of assets, which can be associated to knowing the current condition of the pipelines. In absence of information regarding the condition of pipelines, unforeseen failure can take place making asset replacement inevitable which is the most expensive measure amongst the rest of intervention measures.

In the past, a reactive approach was considered in sewer management as rehabilitation is made upon pipe failure. However, the trend has changed with time towards a proactive approach due to the great cost of repairs at emergencies and its impact on social and environmental aspects. In the current trend, the problems are addressed before their occurrence by implementing a proper asset management system (Vanier, 2001).

Condition assessment models are considered tools that can provide users and decision makers enough information to determine whether an intervention is required for certain pipes based on their state of deterioration. As a result, municipalities need to develop condition assessment models to determine the condition of the assets from which decisions regarding prioritization of inspection, repair and renewal of sewer pipes can be made. These models are built by incorporating data available in databases and records in municipalities. These data are generally the deterioration factors that impact the degradation of sewer pipes and the condition of these pipes. Asset management system for sewer networks is further described in Figure 1-1.

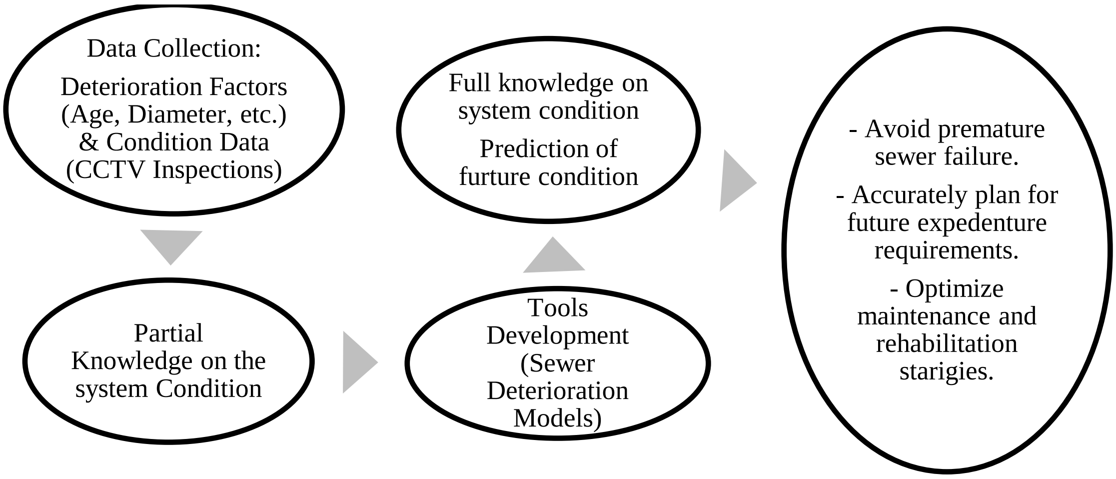


Figure 1-1: Sewer Management System

A reliable inspection plan and condition assessment models for the maintenance and rehabilitation of sewer pipelines is needed to control and minimize adverse potential effects of assets failure as reported by the National Guide to Sustainable Municipal Infrastructure best practice (2003).

Sewer pipelines can be divided into gravity pipelines and pressurized pipelines where each is expected to deteriorate in a different manner. Therefore, two different condition assessment models for each approach were developed to assess the two different pipeline systems. In order to collect the necessary data for the model development, questionnaires were distributed among experts in sewer pipelines in the state of Qatar. Fuzzy Analytic Network Process (FANP) will be used to determine the weight of each of the identified factors that would affect the pipeline condition. The calculated weights (FANP) and effect values will be fed into an Oracle® Crystal Ball software to get a probabilistic condition index for sewer pipelines using Monte-Carlo simulation for the first approach. The calculated weights using (FANP) and generated membership functions for the effect values using Fuzzy Set Theory (FST) will be integrated with Evidential Reasoning (ER) technique to generate the final condition index for the second approach. The main goals of the current study are: (1) to recognize the primary factors that would affect sewer pipelines' conditions and (2) to develop a condition assessment model for sewer pipeline networks.

1.2 Inspection and Evaluation of Existing Sewers

The reasons for carrying out sewer inspections can be divided into three main reasons (Butler et al., 2000):

- Periodic inspection to determine the condition of existing sewer pipelines.
- Crisis inspection to determine the causes behind the failure of sewer pipelines and carry out an emergency repair.
- Inspection of new sewers to check the new sewer pipelines are constructed as per the required workmanship and construction standards.

Several inspection techniques are utilized to assess the condition of sewer pipelines. These techniques can be categorized into three groups.

- Group I: Techniques used to assess the internal condition of sewer pipelines such as Sewer Scanner and Evaluation Technology (SSET), Closed Circuit

Television (CCTV), Zoom Camera, Laser Scanning and Ultra sound. CCTV is the most technique used widely.

- Group II: Techniques used to assess the overall condition of sewer pipelines and the surrounding soil such as Micro Deflections, Natural Vibration and Impact Echo.
- Group III: Techniques used to detect a specific defect within the pipe segment walls such as Ground Penetrating Radar (GPR).

The structural condition of pipes are generally determined through a defined condition assessment rating system. There are several available rating systems such as NEN3399 (1992) and WRc (2001). This assessment usually depends on the results obtained from pipe inspections performed using the technologies listed above. However, those technologies are expensive and time consuming with many drawbacks (Wirahadikusumah, 1998).

Typically, a pipe section is split into 1m length segments where the observed defects resulting from pipe inspections are identified and a condition rating is provided accordingly. The final condition of the pipe is either the rating of the worst segment or the mean rating of all segments.

There are many errors and uncertainties with CCTV inspections' outcome. For example, a certain pipe might appear to be improving in condition with age. Also, there is a possibility that future carried out inspections might not show the defects observed in the current inspections. The uncertainties in CCTV inspections can be connected to two main sources (Chae et al. 2003, Müller and Fischer 2007).

- Human error where the CCTV inspection results depend on the concentration and experience of the operator.

- CCTV camera limitations where the quality of the camera and light condition can lead to inaccurate identifications of the defects.

1.3 Qatar Network Existing Assets

Qatar drainage system is separated in which foul sewage and storm water runoff are collected in separate systems. Sewage generally flows by gravity through house connections to manholes and sewer pipelines. The sewage flows by gravity to pumping stations where it is pumped to Sewage Treatment Works (STW).

Qatar has a flat topography which does not support long distances of gravity sewer as great depths of excavation would be required. Therefore, the sewerage system consists of many pumping station. This leads that for sewage to arrive at the STW, it needs to be pumped several times.

For gravity sewers, the favored material for usage in is vitrified clay (VC), for pipes up to 1000mm diameter where Glass Reinforced Plastic (GRP) is favored for diameters in excess of 1000mm. High-density polyethylene (HDPE) is not preferred, but may be used as a sliplining where trenchless methods are necessary for installation, using concrete jacking pipes. For pressurized pipes, the considered Pipe materials in pumping stations are always Ductile Iron (DI). However, for rising mains outside pumping stations, the piper materials can be either ductile iron (DI) or Glass Reinforced Plastic (GRP) with concrete protection.

Data was collected from the Operation and Maintenance Department in Ashghal Public Work Authority for 2073.352 km of gravity sewer pipelines. Figure 1-2 to Figure 1-5 show the different characteristics (Diameter, Age, Material and Position Relative to Groundwater Table) of sewer pipes for the obtained data set.

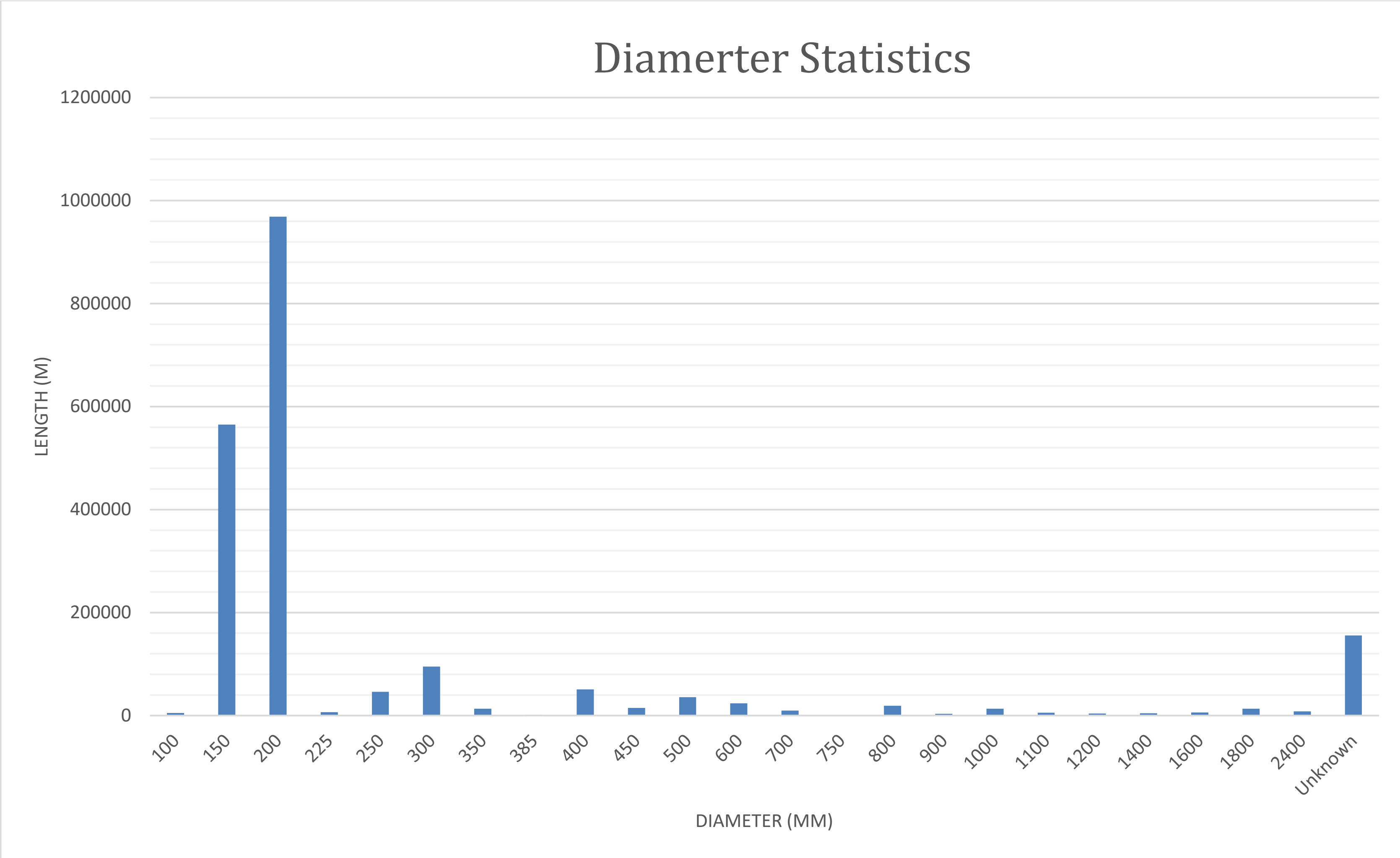


Figure 1-2: Qatar Sewer Network - Diameter Statistics

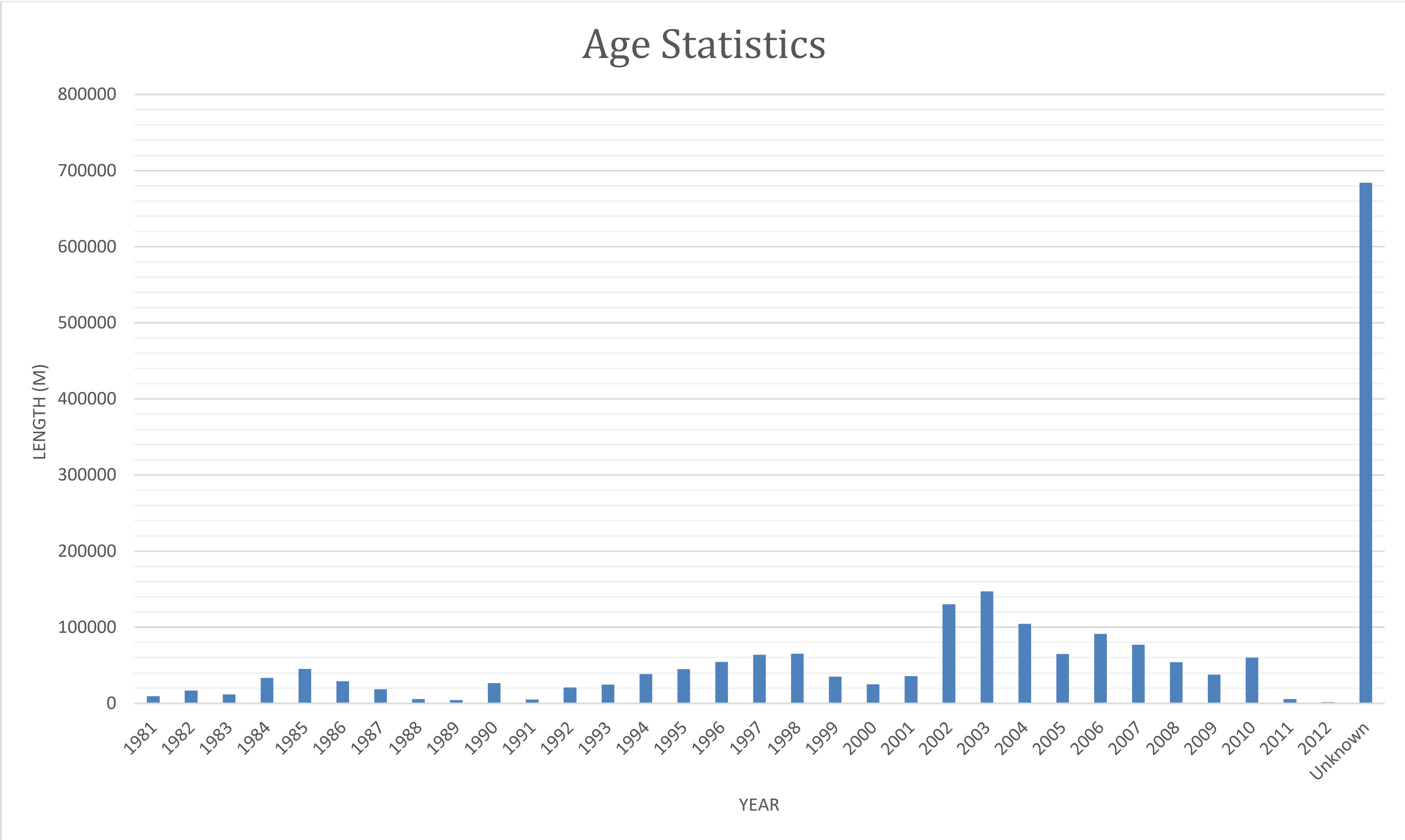


Figure 1-3: Qatar Sewer Network - Age Statistics

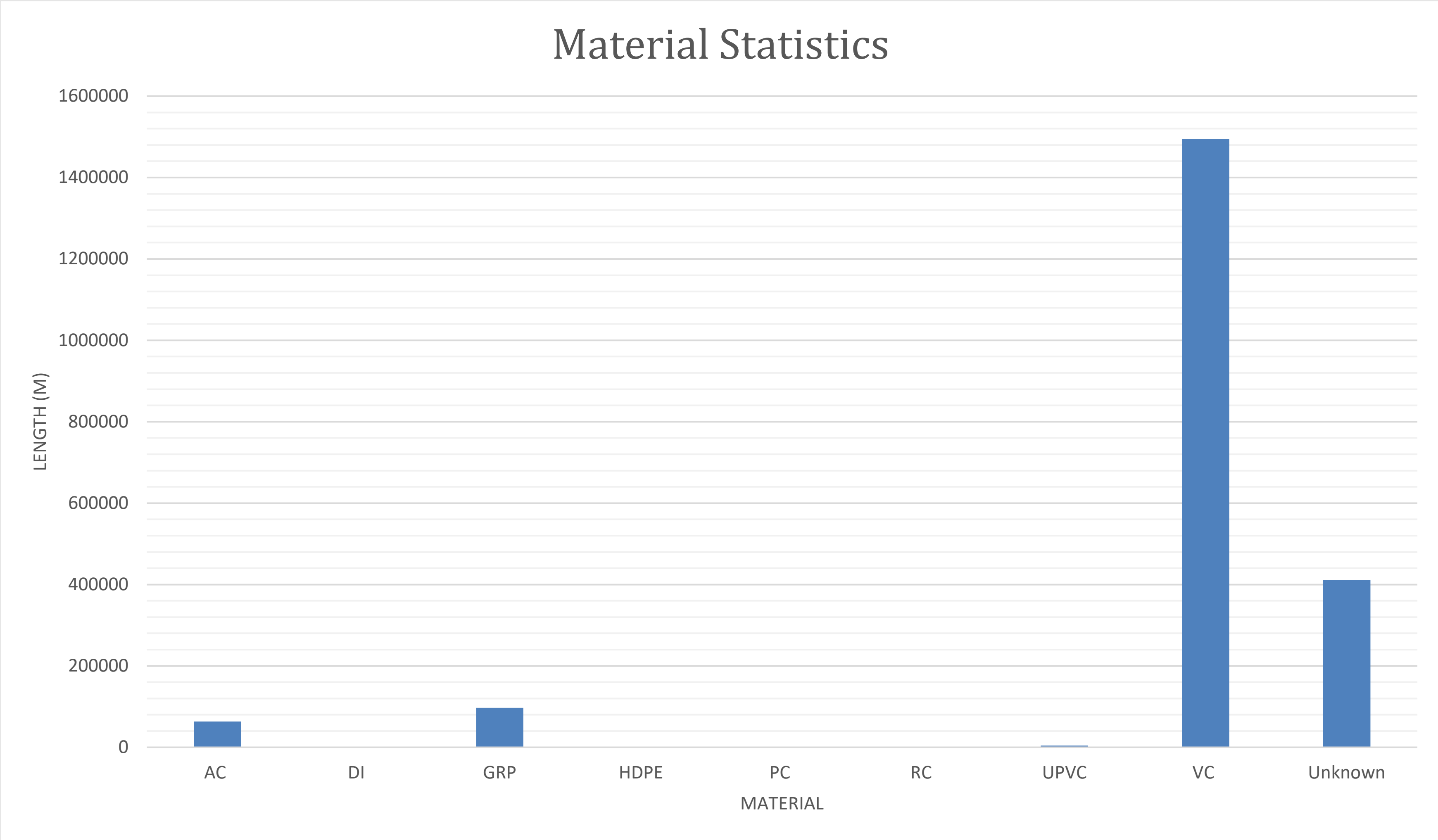


Figure 1-4: Qatar Sewer Network - Material Statistics

AC: Asbestos Cement, DI: Ductile Iron, GRP: Glass Fiber Reinforced Plastic, HDPE: High-Density Polyethylene Pipe, PC: Polymerized Vinyl Chloride, RC: Reinforced Concrete, UPVC: Unplasticized Polymerized Vinyl Chloride, VC: Vitrified Clay.

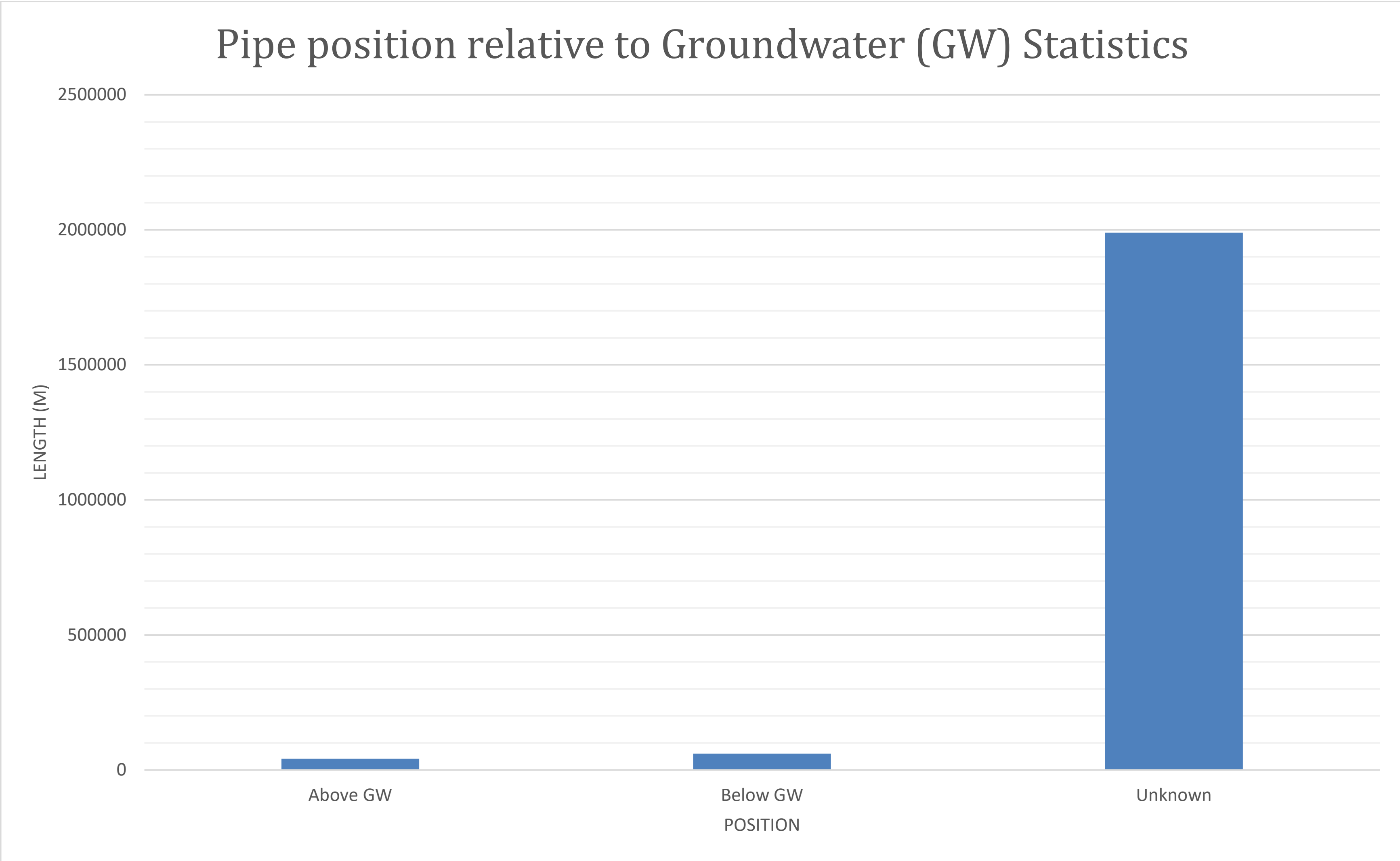


Figure 1-5: Pipe position relative to Groundwater (GW) Statistics

1.4 Thesis Organization

Chapter 1 – Introduction: This chapter includes an overview about sewer network, asset management, inspection techniques and condition assessment models. In addition Qatar sewer network existing assets are identified. Moreover, each Chapter's content is described briefly.

Chapter 2 – Literature Review: This chapter identifies all major factors and sub-factors affecting sewer pipelines' condition and all previously developed condition assessment models. In addition, the limitation of previous researches, the research problem and research objectives are stated.

Chapter 3 – Research Methodology: This chapter describes the research methodology considered in this research.

Chapter 4 – Data Collection: This chapter covers the data collection stage. Questionnaires - one related to gravity sewer pipelines and another related to pressurized sewer pipelines-were constructed and sent to sewer pipelines consultants, consultants, and engineers. The experts were requested to perform a pair-wise comparison among the identified main factors and sub-factors and to determine the effect of each factor on the pipeline condition. In addition, actual data set is collected for validation purposes.

Chapter 5 – Model Development and Implementation: This chapter discusses constructing the condition assessment models using an integrated Fuzzy Analytic Network Process (FANP) and Monte-Carlo simulation as one approach and FANP, fuzzy set theory (FST) and Evidential Reasoning (ER) as another approach.

Chapter 6 – Conclusion: This chapter wraps up the thesis with conclusions.

CHAPTER 2 – LITERATURE REVIEW

2.1 Factors Affecting Sewer Pipelines Condition

In general, pipe deteriorates with age; however pipes with different characteristics can experience significant variations in the deterioration process based on many factors. Hawari et al., (2016) studied and identified major factors affecting sewer pipelines' condition (Fenner, 2000, Fenner et al., 2000, Davies et al., 2001, Ariaratnam et al., 2001, Müller, 2002, Baur and Herz, 2002, Micevski et al., 2002, Hahn, et al., 2002, Baik et al., 2006, Tran et al., 2007, Dirksen and Clemens, 2008, Ana, et al., 2009).

These factors were subdivided into three main groups: (1) physical factors, (2) operational factors and (3) environmental factors. The physical factors included sewer pipeline characteristics such as: age, material type, size, buried depth, coating conditions and installation quality. The operational factors included: flow rate, infiltration and inflow, blockages, corrosive impurities and maintenance strategies in addition to the operating pressure for pipelines under pressure. Finally, the environmental factors included: bedding conditions, location, groundwater level and ground disturbance.

Table 4-1 shows the different variables (e.g.: factors) selected in previous researches. Age, length, material and diameter are the most common factors that were included in these models.

Table 2-1: Variables Included in Sewer Pipelines Condition Assessment Models

Author(s)	Model	Variables Included											
		Age	Diameter	Material	Depth	Length	Bedding	Street Category	Waste Type	Slope	Sewer Type	GWT	Other
Najafi and Kulandaivel (2005)	Artificial Neural Networks	✓	✓	✓	✓	✓				✓	✓		
Ruwanpura et al. (2004)	Rule-Based Simulation	✓		✓		✓							
Hawari et al., (2016)	Rule-Based Simulation	✓	✓	✓	✓	✓	✓	✓		✓		✓	Other Physical, Operational, and Environmental Factors
Hahn et al., (2004)	Expert Systems	Corrosion, Erosion, Defects, Reconstruction and Socio-economic											
Elmasry et al., (2016)	Inference Systems	Structural and Operational Defects											
Ariaratnam et al. (2001)	Regression (Logistic)	✓	✓	✓	✓				✓				
Chughtai and Zayed (2008)	Regression (Multiple Linear)	✓	✓	✓	✓	✓	✓	✓					
Salman (2012)	Regression (Binary and Logistic)	✓	✓	✓	✓	✓		✓		✓	✓		
Ana (2009)	Multiple Discriminant Analysis	✓	✓	✓	✓	✓				✓	✓		Traffic Intensity, Installation Year
Bai et al., (2008)	Evidential Reasoning	Cement lining condition and the Degree of internal corrosion											
Daher (2015)	Fuzzy Based Evidential Reasoning	Structural, Operational, Installation Defects											
Baur and Herz (2002)	Survival Functions	✓		✓				✓		✓	✓		Shape of profile
Wirahadikusumah et al. (2001)	Markov Chains – Nonlinear optimization			✓	✓		✓					✓	
Sinha and McKim (2007)	Markov Chains – Nonlinear optimization	Not Specified											
Kleiner (2001)	Semi-Markov Chains	✓											Expert Opinion
Kleiner et al. (2004)	Fuzzy Rule-Based Markov Chains	✓											
Micevski et al. (2002)	MarkovChains – Metropolis-Hastings Algorithm		✓	✓			✓						Exposure Classification
Baik et al. (2006)	Markov Chains – Ordered Probit	✓	✓	✓		✓				✓			
Le Gat (2008)	Markov Chains – Gompit	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		Installation Period

2.2 Deterioration Models

Prediction of sewer condition is considered a very complex process as it is effected by many factors. A combination of probability based equations and empirical data can be considered for the prediction of sewer pipelines deterioration (Mehle et al., 2001). The basic idea behind deterioration models is to find the relationship between the factors influencing the deterioration process of sewer pipelines and the pipeline condition. Thus, the availability of data containing set of deterioration factors and the sewer pipelines actual observed conditions is considered vital in sewer deterioration modeling. Using the developed models, the future condition of sewer pipelines with respect to age could be estimated. However, each model relies on different concepts and differs in its data requirements and calibration methods (Scheidegger et al., 2011).

Condition assessment models can be classified as physical, statistical or artificial intelligence models (Yang, 2004). Ana and Bauwens (2010) focused on 5 statistical models that have been developed by previous researches to model the structural deterioration of sewer pipelines only in their review which were logistic regression model, multiple discriminant analysis model, cohort survival model, Markov chain model and Semi-Markov chain model. Figure 2-1 shows a classification of the different deterioration models considered in assessing the condition of sewer pipelines.

Physical models are used to define clear quantitative relationship between deterioration factors and condition of sewer pipelines without accounting for the uncertainty of the deterioration process. In contrast, statistical models consider the uncertainties by using probability based equations. On the other hand, artificial intelligence models are considered to be data-driven and not model-driven where the mathematical relationships between the deterioration factors and condition data are evaluated by "learning" the deterioration behavior from inspection data.

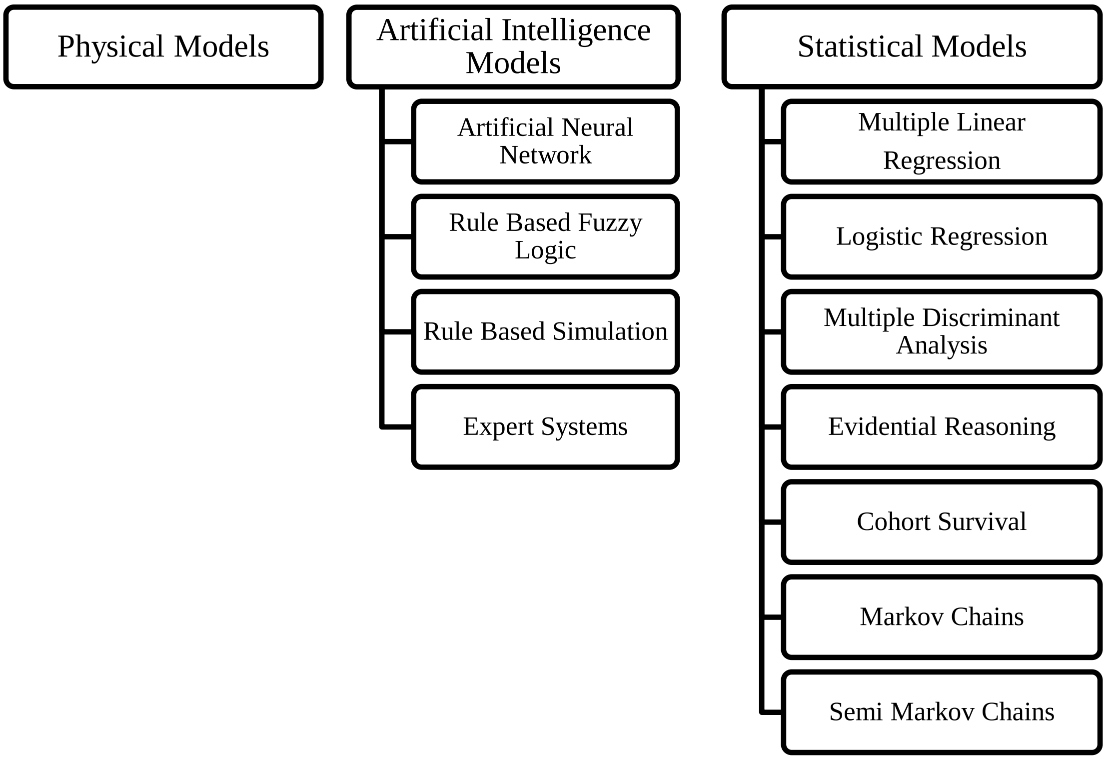


Figure 2-1: Sewer deterioration models' classification

Ana and Bauwens (2010) further classified the deterioration models into two types which are pipe group and pipe level models. Pipe group models consider entire network or cohorts that share similar characteristics such as material, length, size and age and thus experience similar deterioration behavior. Pipe group models can be used by municipalities to set long term strategies and define budget requirements. On the other hand, pipe level models predict the condition of each single pipe, where the pipe characteristics are considered as covariates. Pipe level models are useful in prioritizing inspection and rehabilitation plans and can be converted into group level models by creating groups or cohorts of sewers. All the deterioration models defined in Figure 2-1 are considered as pipe level models that can also be used as pipe group models except for Cohort survival models which fall under pipe group models only.

2.2.1 Physical Models

Model Description:

Physical models are models that consider the physical mechanisms of the deterioration process of sewer pipelines. These physical models are considered deterministic models because they are based on the physical properties and the mechanics of a certain phenomenon. They involve fitting linear or non-linear equations to observations related to the asset failure (Marlow et al., 2009). The pipe structural properties, internal and external loads such as traffic loading and material degradation are the aspects that govern sewer pipes deterioration (Rajani and Kleiner 2001).

Application:

ExtCorr is a physical model that was developed within the Care-S project (Konig, 2005). The developed model could estimate the external corrosion of concrete pipes taking into consideration soil aggressiveness, pipe cement quality and soil moisture. WATS model is another similar application which was developed to simulate the effect of internal corrosion in sewer pipes. The model was based on developing non-linear differential equations describing microbial and chemical transformation processes of organic matter, and chemical compounds resulting from chemical reactions in wastewater (Vollersten and Konig, 2005).

Critique:

Deterioration of sewer pipelines is considered as a complex process that depends on large number of factors (Schmidt, 2009). Some of the aspects that contribute to the condition of sewer pipes can be modeled empirically such as corrosion, but the deterioration in sewer condition itself is very difficult to be modeled in the same manner. Another limitation is the scarcity of data needed to simulate the deterioration mechanisms (Ana, 2009).To overcome such problem, some assumptions are made without taking into consideration the uncertainties associated with asset deterioration and failure (Marlow et al., 2009). As a result, physical models developed to assess the condition of sewer pipelines are considered too simple to reflect the actual deterioration process (Tran, 2007), hence they aren’t practical enough to truly reflect the behavior of sewer pipelines.

2.2.2 Artificial Intelligence Models

Artificial intelligence (AI) aims to develop algorithms that mimic the behavior of humans when dealing with problems and in patterns recognition (Sage, 1990). Artificial Neural Networks (ANN) and rule based models such as fuzzy logic and simulation can be considered as AI techniques.

2.2.2.1 Artificial Neural Networks

Model Description:

The Artificial neural networks (ANN) are a simulation of the human nervous system. They are comprised of artificial neurons which are connected to each other in different layers aiming to mimic human's brain ability to recognize patterns and to recall them in order to predict certain outcomes based on observations (Al-Barqawi and Zayed 2008). The ability of ANN to learn by patterns recognition makes it a very effective tool for model development. ANN could provide predictions based on available historical data when relationships between inputs and outputs aren't clear or distinct enough or when data is incomplete (Sadiq et al. 2004).

In ANN, neurons are linked to each other with connections having a certain weight. When the summations of weights for the inputs reach a certain value, the neurons send a signal that identifies the activation function (Fausset 1994, Zou et al. 2008). In order to determine the weights between connected neurons, the error between the estimated outcome of the model and the actual outcome is minimized (Achim et al. 2007, Salman 2010). In sewer prediction models, the network is trained from a data set containing sewer deterioration factors which represent the input layer and pipe conditions which represent the output layer. Probabilistic neural network (PNN) and back-propagation neural networks (BPNN) are the two main neural networks that have been used in condition assessment modeling. The principles of these PNN and BPNN are presented below:

➢ **Back-propagation neural networks (BPNN):**

In BPNN, the model is divided into three layers as shown in Figure 2-2. The model components are as follow:

- Input layer: Contains a set of nodes representing the deterioration factors having a value of Xi.

- Hidden layer: Each node receives signals from the input layer. The value of each node is the result of the product between the inputs Xi and the associated weights. At each node the sum of the weighted inputs is calculated and an output signal is produced using activation or transfer functions.
- Output layer: The outputs of the hidden layer are received and multiplied by connection weights to define the predicted condition classes.

During the training process, optimization algorithms are used to calibrate the connection weights where the error between the models predicted output and the actual conditions is minimized.

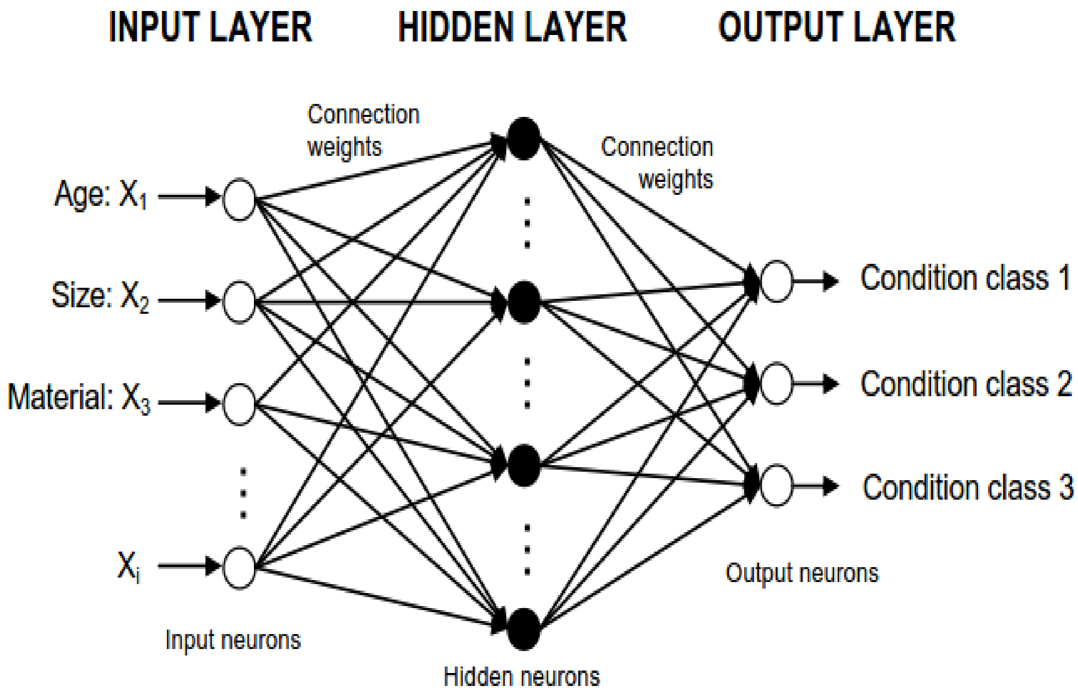


Figure 2-2: Schematic presentation of the back propagation neural network BPNN (Tran et al., 2007)

- **Probabilistic neural network (PNN):**

Probabilistic neural network is defined as a special form of neural networks. It classifies input vectors into classes based on Bayesian classification (Specht, 1990). The model is divided into four layers as shown in Figure 2-3.

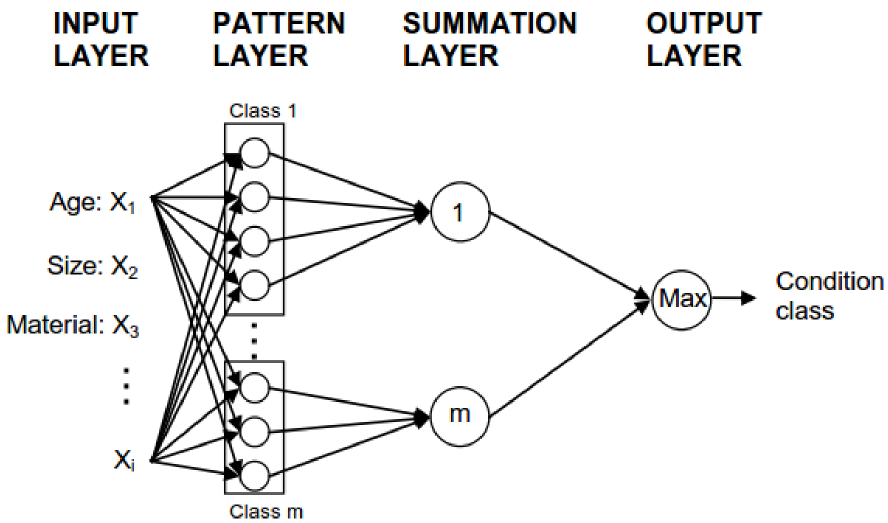


Figure 2-3: Schematic presentation of the probabilistic neural network PNN (Ana, 2009)

The model components are as follow:

- Input layer: Contains a set of nodes where each node represents a deterioration factor having a value Xi.
- Pattern layer: Contains one node for each sample in a training set. The value of each node is the result of the dot product between the input vector X and a weight vector. The nodes are grouped in accordance with their associated class i = 1,2,…..,m.

- Summation layer: Contains a number of nodes where each node represents a condition class. For a given class (i), the outputs of the pattern nodes are received and its value is calculated using an estimation of the probability density function (PDF). Equation 1 shows the mathematical formula of the PDF.

$$f_i(x) = \frac{1}{(2\pi)^{n/2}\sigma^n}\frac{1}{M_i}\sum_{J=1}^{M_i} exp\left[-\frac{(x - x_j^{(i)})^T(x - x_j^{(i)})}{2\sigma^2}\right] \qquad (1)$$

  Where,

  $x_j^{(i)}$: The input vector of the Jth sample in a training set from class i,

  n: The dimension of the input vector,

  M_i: Number of training samples belonging to class i,

  σ: Smoothing parameter which corresponds to the standard deviation of the Gaussian distribution,

  T: Transpose function.

- Output layer: The outputs of the summation layer are received and the condition is assigned by implementing the Bayes decision rule which is shown in Equation 2 for a 2 condition classes.

$$h_1 f_1(x) > h_2 f_2(x) \qquad (2)$$

  Where,

  x: n-dimensional input vector,

  h_i: A priori probabilities that x belongs to a condition class i.

  f_i: Probability density function of class i.

In the PNN, the smoothing parameter (σ) is considered the most important parameter to be determined (Hajmeer and Basheer, 2002). Different values of (σ) are chosen where the network is trained and tested for each value and (σ) is selected based on the results that generate the least misclassification.

Application:

Prediction of the deterioration rates of sewer pipes using ANN based model was developed by Najafi and Kulandaivel (2005). The factors that were considered in the development of this model were age, diameter, length, material, depth, slope, and effluent type. Based on the model results, the diameter of the sewer had the highest importance, while the slope was the least important factor. The model could predict the condition rating of pipelines by entering the seven factors of a specific pipe to the model and the output would be the condition state for this pipe. Structural condition assessment model for sewer pipelines using both Back Propagation Neural Networks (BPNN) and Probabilistic Neural Networks (PNN) was developed by Khan et al. (2010). The two models were built using pipe age, length, depth, diameter, material, and bedding material. The accuracy of the two models was compared based on the outputs of each and it was found that the results from BPNN was more accurate than that from PNN.

Critique:

ANN models are capable of dealing with the pipe deterioration in the absence of clear relationships between inputs and outputs (e.g.: functional relationships aren't identified) (Zou et al., 2008). By analyzing relationships between input and output data, ANN models can identify and replicate complex non-linear processes. However, the models developed using ANNs depend primarily on extensive amount of datasets to create a proper environment to develop such relationships. In addition to this disadvantage, understanding the underlying mechanics in ANN models isn't always easy as they are categorized under 'black box' models due to the fact that they contain hidden underlying processes (Tran, 2007).

2.2.2.2 Rule Based Fuzzy Logic

Model Description:

Fuzzy techniques are mathematical forms that address uncertainties and impreciseness (Zadeh, 1965). Fuzzy rule based modeling, models the relationships between variables using fuzzy if-then rules which follow the term "antecedent proposition". The antecedent proposition is a fuzzy proposition in which (x) (linguistic variable) is expressed in (A) (linguistic constant term). Based on the similarity between (x) and (A), the proposition's value which is between zero and 1 is assigned (Mamdani, 1975). The Mamdani antecedent proposition has the ability to deal with the qualitative and highly uncertain knowledge in the form of if-then rules as shown in Equation 3 (Kleiner, 2007).

$$R_i: if\ x\ is\ A_j\ then\ y\ is\ B_k, i = 1,2, \dots l, j = 1,2, \dots, M, k = 1,2, .. N \tag{3}$$

Where,

x is the input (e.g.: antecedent) linguistic variable,

y is the output (e.g.: consequent) linguistic variable,

A_j is M antecedent linguistic constant in a set A,

B_k is N consequent linguistic constant in a set B,

The values of x, y, A_j and B_k are given the value from predefined sets and rules that define the model. $R_i(x, y)$ is considered as a fuzzy relation in an interval of [0,1], in which R_i is a function of Cartesian ordinates (x, y) taking a value in the interval of [0,1]. To determine the sewer pipelines deterioration, rule based fuzzy techniques models are used in most occasions to overcome the scarcity and impreciseness of data (Kleiner, 2007).

Application:

A condition assessment model was developed using fuzzy based approach by Yan and Vairavamoorthy (2003). In this model, different factors affecting sewer pipeline condition such as age, diameter, material, depth, in addition to other linguistic factors were considered. These linguistic factors were transformed into numerical values through fuzzy rules. A Fuzzy-rule based Markovian process was used to model deterioration of large diameter buried pipelines (Kleiner et al., 2004). The methodology was then applied on sewerage pipelines by Kleiner et al. (2007). The model was built by fuzzifying the age and condition of pipeline into a triangular fuzzy membership functions, from which the deterioration rate of the same pipe was determined. Deterioration rate and current condition states were used to determine the future condition of the pipe. In another research by Rajani et al. (2006), the authors presented the classification of sewer pipelines in fuzzy sets. To achieve such goal, the different distress indicators (e.g.: defects) were converted into fuzzy sets by assigning each distress indicator seven linguistic values which were: excellent, good, adequate, fair, poor, bad, fail based on the defects values. The distress indicators were then aggregated based on the relevant categories where each category would reflect the specific pipe components reflecting the level of deterioration of each category.

Critique:

Although rule based fuzzy models offer a powerful tool to deal with scarcity, impreciseness, and vagueness of data. One of the major shortcomings in using this technique is the subjectivity involved when defining the inference rules which are usually based on experts' opinions. This could lead to ambiguities resulting from human judgements.

2.2.2.3 Rule Based Simulation

Model Description:

The aim of models developed by using rule based simulation is to generate large number of outcomes virtually in order to estimate outcomes as in reality. In the rule based simulation models, a system is defined as a collection of objects which are called entities. The characteristics of these entities are called attributes which define the state of the system for which the change in it would be called a state transition (Inomata et al., 1988). The state of the system and state transitions are called events and usually define the dynamics of the system.

Application:

A rule based simulation model was developed as a condition assessment tool for sewer pipelines by Ruwanpura et al. (2004). The model was developed to determine the condition of sewer pipelines, and the probability that the pipe would remain in its current condition based on 5 years increment. The model was built using three factors which were: age, material and length. Random number generators were used to predict the generate condition rating probabilities of sewer pipelines and were compared with the actual condition rating probabilities. This step was performed several times, to determine the most probable condition rating from the overall number of iteration for a given pipe. Future condition ratings were predicted using Markov chain with the same philosophy that was used in determining the current condition rating probabilities. In another research using rule based simulation, a model was developed using the physical, environmental and operational factors affecting the condition of sewer pipelines to determine their condition states (Hawari, 2016). In this model different factors affecting sewer pipeline conditions were studied and identified and their effect values were determined using Fuzzy Analytical Network Process (FANP). By simulating the product of relative weights and effect values for different factors, several number of iterations, the overall condition of the pipeline was determined.

Critique:

Condition ratings using rule based simulation models can be estimated from limited data points due to the fact that simulation technique depends primarily on generating random probabilities and comparing these probabilities with real data. Nevertheless, data points are assumed to have the same deterioration trend as the adjacent points (e.g.: previous or next data points) which could lead into uncertain results.

2.2.2.4 Expert Systems

Model Description:

Expert systems try to mimic both knowledge and reasoning in an attempt to clone or replace the experts to solve a problem in a specific area (Durkin, 1994). Expert systems usually consists of knowledge base, working memory and inference engines. When solving a problem using expert systems, overlapping rules -usually made of if-then structures are used (Durkin, 1994).

The inference engine in expert systems represents the reasoning in which the system decides to consider the rule or terminate it.

Application:

Hahn et al., (2002) developed a knowledge based expert system using Water Research Center (WRC) factors affecting sewer pipelines conditions (WRC, 2001) to prioritize sewer inspections. The knowledge base in the expert system consisted of six mechanisms, to determine the likelihood and two mechanisms to determine consequences of failure. These mechanisms were derived from interviews with experts and professionals working in the field of sewage pipelines. The inference engine used was Bayesian Belief Network (BBN) to combine the likelihood and consequences of failure to determine the pipelines' risk of failure. In the context of using BBN as an inference engine, Elmasry et al., (2016) employed BBN to determine the structural, operational and overall condition states of sewer pipelines based on defects that could be present in them. To build the BBN, CCTV inspection reports were used to determine the marginal and conditional probabilities for the different variables in the BBN. Monte Carlo Simulation was used to eliminate uncertainties in the estimated probabilities and based on the severities of each defect, the condition states were determined.

Critique:

Expert systems have the ability to pass the knowledge of experts in a certain field leading to efficient and accurate problem solving. Additionally, it can separate knowledge from inference eliminating subjectivity resulting in heuristic problem solving. However, it is only limited to solvable problems (e.g.: can't be used in new research with no prior experience in the area). The aforementioned expert systems models could determine the risk of failure and highlight the critical sections in sewer networks, nevertheless results were compared to real life data and were found to be conservative which could be attributed to the narrow domain that expert systems are subject to, resulting in mistakes.

2.2.3 Statistical Models

2.2.3.1 Multiple Linear Regression

Model Description:

Linear regression finds the linear relationship between the independent variables (effecting factors) and one dependent variable (pipe condition) (Allison, 1999). The multiple linear regression equation general form is presented in Equation 4.

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n + \varepsilon \tag{4}$$

Where,

Y = dependent variable,

α = intercept,

$\beta_1 .... \beta_n$= regression coefficients. Ordinary lest squares method is considered to determine the regression coefficients,

$X_1 .... X_n$= independent variables,

ε = error term.

In modeling the deterioration of an infrastructure asset, the condition state of the infrastructure is the dependent variable of the multiple linear regression equation and the contributing factors that affect the condition of this asset are the independent variables.

Application:

Structural and operational condition assessment models for different sewer pipes materials were developed using multiple regression technique (Chughtai and Zayed, 2007a, 2007b, 2008). The authors used eight factors to develop the structural condition prediction model which were: pipe age, length, diameter, depth, material, material class, bedding factor and street category. However, only pipe material, age, length, diameter and bed slope were used to develop the operational condition prediction model. A best subset analysis was carried out to determine most significant factors that should be included in the developed models as dependent variables.

Critique:

Although ordinary regression provides a flexible and simplistic method to predict the condition rating of sewage pipelines, there are some assumptions made when using such technique that could make the accuracy of the developed model questionable. One of these assumptions is that the distance between consecutive condition states is assumed to be constant, which is not the case in the deterioration of sewage pipelines. Furthermore, error term is assumed to be normally distributed in ordinary regression, which is violated most of the time because ordinary regression is used to model condition states that are considered ordinal response variables. In addition to these limitations, pipe deterioration is a complex process and might not be accurately presented by the linear regression relationship between the independent variables and condition rating (Salman, 2010).

2.2.3.2 Logistic Regression:

Logistic regression can be considered as a special type of linear regression technique where it predicts the outcome of a categorical variable. In logistic regression, dependent variables are transformed into the logit of dichotomous output variable.

2.2.3.2.1 Binary Logistic Regression:

Model Description:

Logistic regression can be used to analyze the relationship between a binary outcome (e.g.: success or failure) and a number of independent variables, which is called binary logistic regression analysis; in such cases. In binary logistic regression models, the outcome variable, (*y*) is categorical and depends on the independent variables, $x_1, x_{2,\ldots}\, x_n$ in a set (*n*). Based on the probabilities associated with the values of (*y*), the outcome variable is calculated. If (*y*)'s value is equal to 1, this means that the pipe is in a good condition state and if the value is 0, this means that it is in a poor condition state. The hypothetical population proportion for which (y = 1) is defined as P(y = 1) = $\boldsymbol{\pi}$. Consequently, P(y = 0) = 1-$\boldsymbol{\pi}$ and the odds of having (y = 1) is equal to ($\frac{\pi}{1-\pi}$). Equation 5 shows the general logit function of binary logistic regression.

$$log\left[\frac{\pi}{1-\pi}\right] = log\left[\frac{p(y=1|x_1,\ldots x_n)}{1-p(y=1|x_1,\ldots x_n)}\right] = \alpha + \beta_1 X_1 + \beta_2 X_2 \ldots. + \beta_p X_p$$

$$= \sum_{j=1}^{p} \beta_j x_j \qquad (5)$$

Where,

α is the intercept parameter.

β_s are the regression coefficients associated with the *n* independent variables.

The probability of (y =1) can be determined by using an exponential transformation, as shown in Equation 6.

$$P(y = 1|x_1 \ldots\ldots x_n) = e\,\frac{\alpha+\sum_{j-1}^{n}\beta_j x_j}{1+e^{\alpha+\sum_{j-1}^{n}\beta_j x_j}} \quad (6)$$

Where,

α and β are parameters estimated from data using the maximum likelihood estimation (MLE).

Application:

Logistic regression technique was used to predict the probability of sewer pipes to be in a certain state (Ariaratnam et al., 2001). The authors in this research used age, diameter, material, waste type, and average depth of cover as the contributing factors that would affect the condition of sewer pipes. Wald test was used to examine the significance of the coefficients of the independent variables in logistic regression model. It was found that the depth and material were not significant and that the coefficient of age increases the odds of deficiency by 2.6% per year.

A binary logistic regression model was also developed for the prediction of the probability that a sewer pipeline would be in a deficient state for Edmonton, Canada. The model was developed for the intent of inspection prioritization (Ariaratnam et al., 2001).

2.2.3.2.2 Multinomial logistic regression

Model Description:

Multinomial logistic regression is an extension of binary logistic regression and can be used when dependent variable is categorical and has more than two levels. For a dependent variable with (k) categories, the multinomial regression model estimates (k-1) logit equations. A generation of (k-1) logits from the remaining (k – 1) categories can be determined as per Equation 7.

$$ln\frac{\mathrm{P(Y = i|x_1 \dots \dots x_n)}}{\mathrm{P(Y = k|x_1 \dots \dots x_n)}} = \beta_0 + \beta_{i1}x_1 + \beta_{i2}x_2 + \cdots . + \beta_{in}x_n \qquad (7)$$

Where,

i = 1, 2, …, k – 1 correspond to categories of the dependent variable,

x_s are independent variables,

n is the number of independent variables,

β_0 is the intercept for category i,

β_{is} are the regression coefficients of independent variables defined for each category i.

β_0 and β_{is} values for each (k – 1) logit equation can be estimated by multinomial logistic regression (Agresti, 2002).

Therefore for a dependent variable with (k) levels and a total number of (p) independent variables, the multinomial logistic regression models estimate (k – 1) intercepts, and p*(k – 1) regression coefficients. Calculation of probabilities associated with each category of the dependent variable is shown in Equations 8 and 9.

$$\mathrm{P(Y = i|x_1 \dots x_n) = \pi_i(x) = \frac{\exp(\beta_0 + \beta_{i1}x_1 + \beta_{i2}x_2 + \cdots . + \beta_{in}x_n)}{[1 + \sum_{i=1}^{k-1}(\beta_0 + \beta_{i1}x_1 + \beta_{i2}x_2 + \cdots . + \beta_{in}x_n)]}} \qquad (8)$$

$$\mathrm{for\ i = 1,2, \dots k - 1}$$

$$\mathrm{P(Y = k) = \pi_k(x) = \frac{1}{[1 + \sum_{i=1}^{k-1}(\beta_0 + \beta_{i1}x_1 + \beta_{i2}x_2 + \cdots . + \beta_{in}x_n)]}} \qquad (9)$$

$$\mathrm{for\ i = k}$$

Application:

Multinomial logistic regression was used to develop a model for predicting the financial needs for rehabilitation of sewage network over a specific planning horizon of years (El-Assaly et al., 2006). The cost in this model was estimated as the product of the predicted defected pipe and the cost of the repair method for the same pipe. Different pipes were arranged in an ascending order to determine the ones with the highest cost, which would require rehabilitation. Using the same technique, a model for sewer pipes deterioration was used to determine risk of failure of pipes considering the different geographical, physical, and functional factors affecting sewer pipes using both multinomial logistic regression, and binary logistic regression (Salman, 2010). Logistic regression gave the most accurate results when probability of failure was estimated.

Critique:

Logistic regression analysis helps in identifying the most important variables affecting the sewer pipelines condition which provides a better understanding for the trend of the deterioration process. In addition, no assumptions are made on the distributions of the independent variables which can be considered as one of the main advantages of this technique. The main disadvantage of using this technique is that a satisfactory amount of data for the factors affecting sewer deterioration is required in order to build the model, which sometimes is considered a challenge in some municipalities due to poor filing system and documentation.

2.2.3.2.3 Multiple Discriminant Analysis

Model Description:

Multiple discriminant analysis is used to analyze the linear relationship between a dependent categorical variable (e.g. pipe condition) and a number of predictor variables (e.g. deterioration factors). This method is similar to multinomial logistic regression technique, since more than two outcomes can be handled. The model is constructed based on available observations set in which the outcome is known. Functions are constructed using a set of linear functions of the predictor set, where these functions are called classification functions as shown in Equation 10.

$$L_i = \beta_0 + \beta_{i1}x_1 + \beta_{i2}x_2 + \cdots . + \beta_{in}x_n \quad (10)$$

Where,

L_i is the classification function score for class (i)(i = 1 to k-1, with k being the number of classes),

x_i are the predictor variables,

β_{ij} are classification coefficients corresponding to n-number of predictors variables and β_0 is a constant.

The methodology behind this multiple discriminant analysis is described in Figure 2-4. Any observation could be visualized in an n-dimensional space where the axes are the classification functions (L_i). Figure 2-4 shows three different classes, consequently only two classification functions are required (L_1 and L_2) to classify the observations. Since, the new prediction is closer to the centroid of class 3, the prediction outcome would be 3.

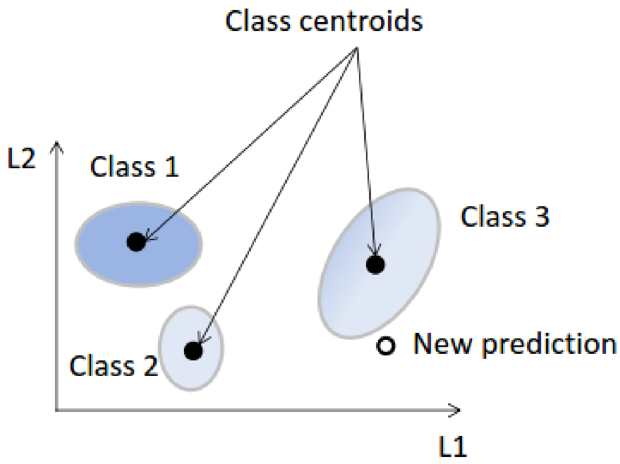


Figure 2-4: Multiple discriminant analysis visualization (Tran, 2007)

Application:

Multiple discriminant analysis was employed to model the deterioration of gravity pipelines in Australia by Tran et al. (2007). The predictor variables included diameter, age, depth, slope, location, roots of trees, soil properties and hydraulic condition. Unfortunately, this model showed low accuracy with less than 50% prediction abilities. It was found that the pipe age was insignificant which comes in line with the low accuracy, while the most significant factor was found to be the hydraulic condition. Also, it was applied by Ana (2009) to predict the condition of sewer pipes in Leuven and Antwrep among other techniques to compare between the suitability of using them in prediction.

Critique:

Models developed using multiple discriminant analysis could provide direct information about the score and class for the state of the pipes, not in the form of probabilities unlike logistic regression models. It can also provide information on the most important variables affecting the deterioration process which helps in better understanding the pipe deterioration trend. Not only does multiple discriminant analysis require sufficient set of data and linearity similar to the ones required in logistic regression technique, but also there should be normality and lack of multi-collinearity between independent variables which can be considered as one of the major drawbacks in the application of this method. If the normality assumptions are satisfied, multiple discriminant analysis is expected to give better predictions. Otherwise, logistic regression would be more suitable (Pohar et al., 2004).

2.2.3.3 Evidential Reasoning

Model Description:

Evidential reasoning describes and handles various types of uncertainties by using the concept of the degrees of belief, in which each attribute of an alternative of a multi criteria decision making problem is described by a distributed assessment using a belief structure. Unlike conventional approaches that require scaling grades and averaging scores to aggregate attributes, the evidential reasoning approach aggregates belief degrees by employing an evidential reasoning algorithm.

It aggregates two factors at a time and the resulting aggregation of the first two factors of evidence is aggregated with the third factor of evidence and so on. Equations 11, 12 and 13 show Dempster-Shafer rule combination of two basic probability assignments which is the theory used in developing the evidential reasoning algorithm.

$$m_{12}(\Psi) = m_1(\Psi) \oplus m_2(\Psi) \tag{11}$$

$$= 0, \text{ when } \Psi = \Phi \tag{12}$$

$$= \frac{\sum_{A\cap B=\Psi,A,B\subseteq\oplus} m_1(A)m_2(B)}{1-k} \ \Psi = \Phi \tag{13}$$

Where,

k = $\sum_{A\cap B=\Psi,A,B\subseteq\oplus} m_1(A)m_2(B)$, representing the conflict between subsets A and B, $m_1(\Psi)m_2(\Psi)$ two basic probabilities to a subset Ψ.

From the above equations, the evidential reasoning general equation for evaluating an attribute with contributing factors can be given by Equation 14.

$$E_k = e_k^1 \oplus e_k^2 \oplus e_k^3 \oplus \dots\dots e_k^{l_k} \tag{14}$$

Where,

$l_k$denotes the number of factors that contribute to the k^{th}attribute,

e_k^i is the evaluation of each contributing factor (i+)

Application:

A condition assessment model of buried pipes using hierarchical evidential reasoning was developed by Bai, et al., (2008). Inferences for condition assessment was done using the hierarchical evidential reasoning approach that employed the Dempster-Shafer theory. The developed model was built using a hierarchical framework for pipe condition assessment in which all contributing factors/attributes were assumed independent, and only the parallel aggregation of factors/attributes were performed using Dempster-Shafer rule of combination. This model took into considerations, factors that affect the integrity of pipelines wall such as cement lining condition and the degree of internal corrosion. Evidential reasoning using fuzzy set theory was used to determine the overall pipeline conditions using possible defects (Daher, 2015). Defects that could be present in different pipeline components were divided into three categories namely structural, operational and installation defects. The different defect families and categories along with the sewer pipeline components were given weights based on their relative importance and how they contribute to the overall condition of the pipelines. Fuzzy based evidential reasoning was used to aggregate the different defects in the respective pipeline components from which the overall pipeline condition and each of the structural, operational and installation condition of different components were determined.

Critique:

Evidential reasoning is capable of dealing with incomplete and conflicting evidence without having to make any assumptions about missing data. In addition, they could combine multiple bodies of evidence. One of the major disadvantages of using hierarchical evidential reasoning is its inability to deal with dependent factors as well as the conflict between them without using auxiliary rules of combination.

2.2.3.4 Cohort Survival

Model Description:

Cohort survival model is used to describe the process of sewer deterioration for homogeneous pipes having similar characteristics (e.g. cohorts). It is assumed that sewer cohorts with certain probability survive a number of years in a certain condition state. These cohorts pass through successive transitions, from the current condition state to a worst condition state during their service life (Baur et al., 2004). This transition is described by condition survival curves which are known as transition functions. The transition function applied in assessing conditions of pipelines of the Herz distribution is given by Equation 15 (Herz, 1995 and 1996).

$$S(t)_{i\rightarrow i+1} = \frac{a_{i\rightarrow i+1} + 1}{a_{i\rightarrow i+1} + e^{b_{i\rightarrow i+1}(t - c_{i\rightarrow i+1})}} \tag{15}$$

Where,

$S(t)_{i\rightarrow i+1}$ is the fraction of pipes at age t which have survived until condition i or better,

A is the aging factor (a = 0 means that no aging takes place),

B is the transition parameter (the transition is faster when b is large),

C is the resistance time which determines the age where no further deterioration is anticipated.

Each different cohorts require calibration of the parameters a, b and c of the Herz transition function. This could be performed by minimizing the deviation between the fraction of sewers at certain condition i between the expected values yielded from the model and actual data. Only installation year, inspection year and the condition state are required to build the survival functions, unlike the previous discussed methods.

Application:

Several tools have been developed using cohort survival models that have been implemented by Horold, (1998) and Horold and Baur (1999). The transition curves developed for Norwegian network shown in Figure 2-5 was used to determine the remaining service life for sewer pipes towards reaching the worst condition states. For instance, the 50 years old group of sewers were found to be in condition state 3 from CCTV inspections. The first pipe in this group to reach condition 5 was estimated to be after 48 years which represents the minimal remaining service life (RSL).

Similarly, the last pipe within the group was anticipated to reach condition 5 after 105 years which represents the maximum RSL. The average RSL of the group was determined by measuring the horizontal distance from the middle of the group to the transition curve representing condition 5. From this, it is recommended to use the average RSL when planning for future maintenance (Jansen, 2007).

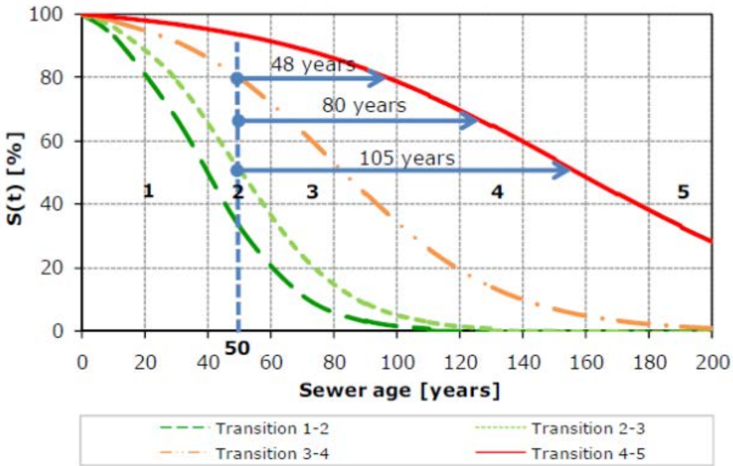


Figure 2-5: Norwegian network's transition curves (Horold, 1998)

Equation 15 was used in the analysis of an existing sewage network in Germany to assess the condition of this network (Baur and Herz, 2002). Weighted least squares method was used to estimate the parameters of transition functions. The rate by which the pipes age was calculated by determining the midpoint of two areas. The first area was bound between the transition curves corresponding to the transition from previous condition state to current condition state and the second area was bound between current condition state and the next condition state. As for the residual life of the pipes, it was predicted based on the rate of pipes' aging.

Critique:

The simplicity in the concept behind the development of cohort survival model is considered one of the main advantages. However, significant amount of inspection data are needed for each cohort in each condition state to properly calibrate the transition functions (Fenner, 2000). The main difficulty in developing cohort survival models arises from the lack of inspected data of certain conditions, since the operator tend to concentrate his inspections on specific sewer types such as old sewers and sewers in poor conditions (Ana and Bauwens, 2010). Also, there is usually an underestimation of the pipes in worst condition state as they may have already collapsed and were not included in the data under study. Consequently, there would be an overestimation in the predicted survival rates and remaining service life. A correcting model calibration has been suggested to fix this anomaly which is referred to as selective survival bias by adding weights to the model (Le Gat, 2008).

2.2.3.5 Markov Chains

Model Description:

Markov chain is a stochastic process which has been used to describe the deterioration of sewer pipes passing through a number of condition states. This process could be described as 'memoryless' as the conditional probability that an asset could have in the future depends only on its current condition (Ross 2000). In Markov chains, a transition probability matrix represents the probability values for an asset to remain in its current condition state or transfer to another condition state. The general form of a transition matrix can be expressed by Equations 16 and 17.

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \ldots & \ldots & \ldots & \ldots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix} \quad (16)$$

$$\sum_{j=1}^{m} p_{ij} = 1 \; (for\; i = 1,2,3, \ldots m) \quad (17)$$

Where,

p_{ij} is the conditional probability of an asset to be in condition state (j) with a current state (i) after a unit transition period.

The transition probabilities can be either time dependent (non-homogeneous Markov model) or time independent (homogeneous Markov model) (Ana and Bauwens, 2010). Since pipe deterioration is age-dependent as new pipes deteriorate slower than older pipes, time dependent Markov model is considered to be more representative (Kleiner, 2001).

In pipe deterioration, transition can only occur from the current condition state to worst condition states as it is impossible for a pipe to improve its condition without interventions. Therefore, p_{ij} is considered as 0 for i > j. Also, the pipe cannot further deteriorate in condition after reaching the worst condition state (m). Thus, the transition probability p_{mm} = 1. Hence the non-homogeneous transition probability matrix can be expressed by Equation 18.

$$p_{ij}^{t,t+1} = \begin{bmatrix} p_{11}^{t.t+1} & p_{12}^{t.t+1} & \ldots & p_{1m}^{t.t+1} \\ 0 & p_{22}^{t.t+1} & \ldots & p_{2m}^{t.t+1} \\ \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & \ldots & 1 \end{bmatrix} \quad (18)$$

Further simplified form of the transition matrix has been considered by assuming that the transfer in condition only drops one level at a time (Wirahadikusumah et al., 2001 and Le Gat, 2008). This can be expressed by Equation 19.

$$p_{ij}^{t,t+1} = \begin{bmatrix} p_{11}^{t.t+1} & p_{12}^{t.t+1} & 0 & \dots & 0 \\ 0 & p_{22}^{t.t+1} & p_{23}^{t.t+1} & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & \dots & \dots & p_{m-1,m-1}^{t.t+1} & p_{m-1,m}^{t.t+1} \\ 0 & 0 & \dots & 0 & 1 \end{bmatrix} \quad (19)$$

However, the above might not be appropriate to model structural deterioration as the pipe might deteriorate by several condition states at a single time step (Micevski et al., 2002). To solve this problem, Kleiner (2001) has recommended the use of short transition periods where only deterioration by a single condition state is anticipated. This can be expressed by Equations 20 to 22.

$$Q(t) = \{q_1, q_2, \dots q_m\} \quad (20)$$

$$Q(t+s) = Q(t)p^{t,t+1}p^{t+1,t+2} \dots p^{t+s-1,t+s} \quad (21)$$

$$E(t+s) = Q(t+s)S^T \quad (22)$$

Where,

$Q(t)$ is the probability mass function (pmf),

q_i is the probability of the system being in state i at time t,

$Q(t+s)$ is the probability mass function after s time steps.

<u>*Application:*</u>

Deterioration of large diameter combined sewers was modeled using Markov chains by Wirahadikusumah et al. (2001). Because Markov Chains can be used to model deterioration of pipelines on a network level, the data used in building the model were categorized into sixteen groups based on material, groundwater table level, backfill soil type and the depth. Regression analysis was performed to determine the relationship between condition rating and time where non-linear optimization was used to convert the relationship between condition states and time into a Markov-chain model. Probabilities in the transition matrix were determined by minimizing the sum of the absolute differences values between the condition states which were estimated using exponential functions and Markov-chain model estimations.

In another condition assessment model that was developed for sewer pipelines in Waterloo, Canada, transition probabilities in Markov Chains were determined by minimizing the sum of the absolute differences values between the condition states which were estimated using polynomial regression and Markov-chain model estimations (Sinha and McKim, 2007). Kleiner et al., (2004) modeled the deterioration of buried infrastructures by employing a fuzzy-rule based non-homogenous Markovian process to which was then applied on sewage pipelines to determine their condition states (Kleiner et al., 2007). The age and condition of the pipe were modeled using triangular fuzzy sets and the deterioration rate of the pipe was determined by using a fuzzy rule set. Future condition state was determined based on the deterioration rate value obtained from this procedure and the current condition state. Pipe physical properties such as age, diameter, material and slope were used to calculate the transition probabilities to be used in Markov Chain model for the deterioration of sewer pipelines (Baik et al., 2006). Similar to this methodology, a research was carried out in which the transition probabilities were obtained using Gompertz distribution and were calibrated using diameter, sewer type and installation period (Le Gat, 2008).

Critique:

Modeling sewer pipelines deterioration using Markov's chain allows the modeling of complex and chronological events which could help in capturing the deterioration behavior of sewer pipelines. One of the difficulties in using Markov chains is determining the transitional probability matrix. Also, the absence of previous historical inspection records could increase the challenges accompanying the use of Markov chains which would be more noticeable if dataset should be divided into cohorts (e.g.: clusters of same characteristics) and for each cohort, new Markov-chain deterioration curve has to be generated. However, such limitation could be solved by using an additional technique to estimate transition probability values, nevertheless the results could be affected greatly based on the chosen technique. Additionally, unless different transition matrices are applied for different time steps, the deterioration rate is assumed to be time independent which doesn't truly represent the dynamic nature of deterioration in sewer pipelines.

2.2.3.6 Semi Markov Chains

Model Description:

The semi Markov chain is similar to the Markov chain with the ability of modeling the waiting time that an asset would spend in a certain state. This waiting time is usually considered to follow a random distribution (Lawless, 1982). When modeling sewer pipelines deterioration using semi Markov chains, pipelines are assumed to spend a random interval in each state that can be translated into a probability distribution. Equation 23 shows the mathematical formulation of the cumulative waiting time of an asset in a certain state with a deterioration trend following semi Markov chain.

$$T_{i-k} = \sum_{j=i}^{k-1} T_{j,j+1}, \text{ i} = \{1,2,...,m-1\}, \text{ k} = \{2,3,...,m\} \quad (23)$$

In this equation the cumulative time is represented as a cumulative distribution for the random variable T_{i-k}which represents the time that an asset would take to transfer from state (i) to state (k).

Application:

Deterioration of large buried pipelines has been modeled using semi Markov chains, where the transition probabilities were linked to their age (Kleiner, 2001). In order to model the transition probabilities in a certain state (i) at a time (t) to another condition state (j) at a time (t+1), Equation 24 was used.

$$p_{i,i+1} = \frac{f_{1-i}(T_{1-i})}{S_{1-i}(T_{1-i}) - S_{1-(i-1)}(T_{1-(i-1)})} \quad (24)$$

Where,

$p_{i,i+1}$ is the transition probability of the asset from a certain state to the next one,

$f_{1-i}(T_{1-i})$ is the probability density function of the variable (T_{1-i}).

In this model, the transition probabilities were derived with the aid of Weibull distribution that was used to determine the distribution of waiting times, where expert's opinions were used to determine the Weibull distribution's parameters. The sum of waiting time in different states of the asset which represented the cumulative probability function was calculated using Monte-Carlo simulation.

Critique:

In semi-Markov chain, lack of data problem required for determining transition probability can be solved by using the expert's opinions. However, in order to determine the distribution of waiting time in the developed models, adequate dataset is required for the condition of pipes and history of inspections which might be considered as a challenge because of absence of historical records for inspected pipelines.

2.2.4 Summary

This section presented the different physical, artificial intelligence and statistical models developed to assess the condition of sewer pipelines. In addition, factors affecting the condition of sewer considered in previous studies were determined. Age, length, material and diameter are the most common factors that were included in these models.

The models discussed in this chapter can be divided into two types namely: pipe level models and pipe group models. In the pipe level models, the condition is assessed for individual pipes without considering the global deterioration of the network which could be suitable for scheduling inspections and optimizing the rehabilitation or inspection policies with respect to the number of pipelines addressed. While, in the pipe group level models, the condition of the whole network is assessed based on pipelines with similar characteristics from which strategic decisions can be made regarding budgetary allocation for the network rehabilitation and maintenance.

Table 2-2 shows a classification for the different techniques used in developing condition assessment models for sewer pipelines from the aforementioned perspective. It can be noticed from the table that, models such as survival functions and discriminant analysis provide the life expectancy of pipelines and predict the condition state of pipes while logistic regression models could assess the probability of failure making it much more suitable to be used in risk based management of sewer pipelines than the former two models.

Table 2-2: Assessed Levels and Expected Outcomes for Each Condition Assessment Model

		Rule Based			**Regression**					
Models	**ANN**	**Simulation**	**Fuzzy**	**Expert Systems**	**Multiple**	**Logistic**	**Multiple Discriminant Analysis**	**Evidential Reasoning**	**Survival Function**	**Markov Chains**
Pipe Level	✓	✓	✓	✓	✓	✓	✓	✓		✓
Network Level	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Output from the Model	Condition Sate of individual pipes or pipe cohorts	Condition State of individual pipes or pipe cohorts			Condition State of individual pipes	Probability of failure of individual pipes or pipe cohorts	Condition Sate of individual pipes or pipe cohorts		Remaining Life time of pipelines and Proportions of each pipe at certain condition state	Condition Sate of individual pipes or pipe cohorts

2.3 Problem Statement

The presence of condition assessment models can help in managing assets and avoiding early failure. It can also provide an accurate prediction of expenses required in the future through understanding and predicting the remaining asset life and its condition. Condition assessment models can help in better maintenance and rehabilitation strategies by determining the required corrective actions (i.e.: maintenance, rehabilitation, renewal) and their timeframes.

One of the drawbacks to depend on these models in assessing the condition of sewer pipelines is that one of the main sources of gathering information about factors are data from CCTV inspection reports which could be either incomplete or ambiguous resulting in erroneous and uncertain models. Additionally, sometimes gathering such data is costly or could be hard, which would raise the issue of data reliability.

The problem of data availability is considered one of the challenges that is worsened when dealing with pipe group level models that require categorizing pipelines into cohorts based on their characteristics. Therefore and to develop a reliable condition assessment model, regular inspections have to be performed and new emerging technologies would be required to facilitate gathering required information in a complete and accurate manner. The concept of Artificial intelligence makes models such as ANN, simulation and fuzzy based more robust and computationally efficient when compared to the statistical ones. However, one of the main disadvantages is their need for extensive datasets and the difficulty in understanding the underlying mechanics in these models. Logistic regression, multiple discriminant analysis, and Markov chains are different techniques that can be used to determine the condition state of pipelines in a network, however an adequate amount of data regarding the factors affecting sewer deterioration is required and in some cases the computational efforts are large especially in large scale networks.

There is a crucial need to develop and integrated condition assessment models that overcome these setbacks. The proposed condition assessment models in this study were built based on the experience of specialists working in different fields in drainage networks to overcome the problem of data availability as the collected data sets were only used for validation purposes. In addition, the proposed condition assessment models are intended to complement the efforts of others by including new factors and taking into consideration their interdependencies and minimizing the uncertainties.

2.4 Research Objectives

The main objective is to build condition assessment models that are expected to be a useful tool for decision makers to properly plan for their inspections and provide effective rehabilitation of sewer networks. The sub-objectives of this research can be summarized as follows:

- To identify and study the different factors affecting sewer pipeline condition and their severities.
- To identify and study the previously developed condition assessment models.
- To model and assess sewer pipeline condition based on the identified factors.
- To develop new condition assessment models.

CHAPTER 3 – RESEARCH METHODOLOGY

The research methodology to develop condition assessment models using FANP and Monte-Carlo as the first approach and FANP, fuzzy set theory (FST) and Evidential Reasoning (ER) as the second approach is described in Figure 3-1. A description of the adopted methodology is further described below.

To develop a condition assessment model for sewer pipelines, the factors contributing to the deterioration of pipelines and their effects are integrated to develop an index to represent the condition of pipeline under study. The first part of the methodology for both approaches was identifying and collecting data related to the factors that would affect and deteriorate sewage pipelines. After identifying these factors, two questionnaires - one related to gravity sewer pipelines and another related to pressurized sewer pipelines were distributed to experts working in the field of infrastructures and sewage networks to collect the relevant data required in model development (i.e.: weights, relative importance, and effect of the contributing factors. FANP was used to address the interdependency between different factors affecting sewer pipelines conditions and uncertainty when processing data elicited from human judgment (i.e.: transforming a verbal pairwise comparison judgment into an exact ratio representing the strength of the alternative when compared to another) in an attempt to overcome the setbacks that could be encountered when applying Analytical network process (ANP) solely. The developed models take into consideration the interdependencies between three factorial groups affecting sewer pipeline conditions, namely, physical, operational and environmental. FANP integrated with Monte-Carlo

Simulation are used to determine the relative weights of these factors. The rest of the methodology adopted for the first and second approaches differs.

For the first approach, using calculated weights and effect values; probabilistic condition index for sewer pipelines is determined with the aid of Monte-Carlo simulation. The outcome generated by Monte Carlo Simulation would form different probability distributions based on a random sample collection. By determining the most frequent outcome, the user can see and analyze the range of certainty and biasness of the simulated outcome that would help in eliminating the uncertainty that accompanies the model output, thus came the rationale behind utilizing Monte-Carlo simulation. The assessed pipeline condition in the form of a probability distribution function is the output of the model.

For the second approach, FST is used to assign the fuzzy membership functions and thresholds for the severity of the factors' effects on the pipelines condition. In order to combine both the effect values and relative weights of factors affecting sewage pipelines, ER is used as an aggregation technique. It is used to determine the degrees of belief for the model outputs that represents the user's certainty level about how good the condition of the pipeline is, based on the effect value of the different contributing factors. After combining all the factors degrees of belief, defuzzification using the FST to generate a final crisp condition index is carried out.

Finally, the developed model is validated using data collected from an existing sewage network in the city of Doha, Qatar. The validation set included actual conditions for 549 gravity pipelines with 6 available factors which are: age, diameter, length, and buried depth, pipeline position relative to groundwater and pipeline material. In addition to the pipeline actual condition obtained from CCTV analysis.

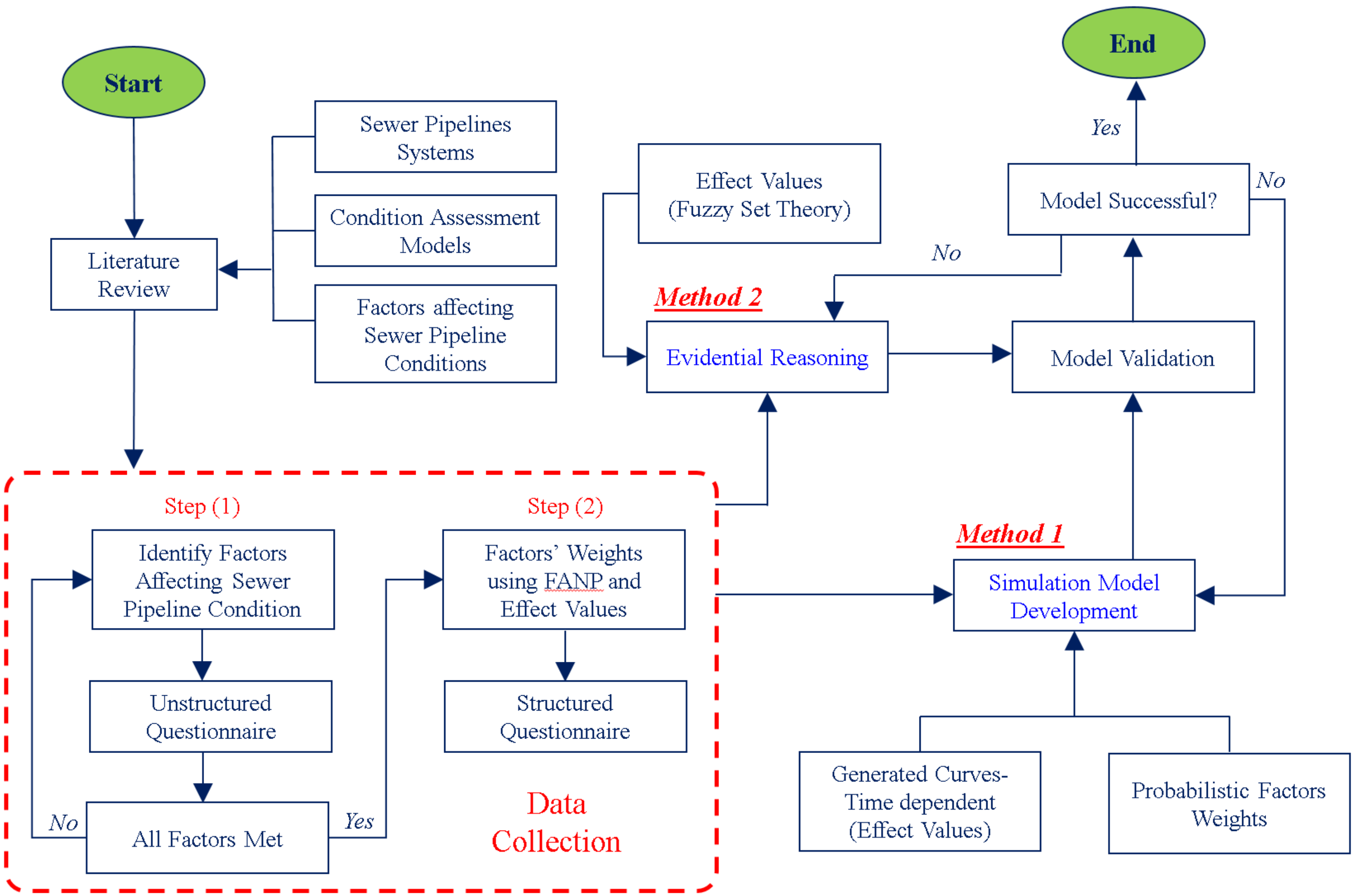


Figure 3-1: Research Methodology

CHAPTER 4 – DATA COLLECTION

4.1 Overview

To achieve the main objectives of this research which is developing condition assessment models for sewer pipelines, all Factors affecting gravity and pressurized pipelines in sewage networks were studied and included in a questionnaire. A questionnaire was distributed to experts in the field, to determine the weights of the identified factors and the severity of their effect on sewage pipeline condition. In addition, the developed model were validated through a collected data set. This chapter describes the data collection phase in details.

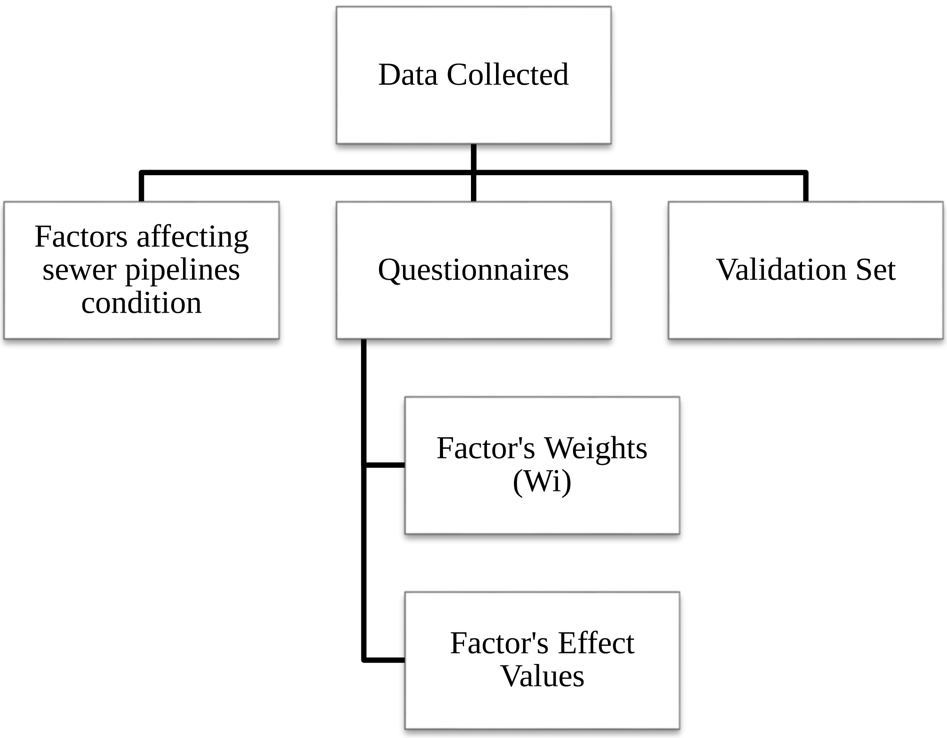


Figure 4-1: Types of Data Collected

4.2 Factors affecting sewer pipelines condition

Identified factors affecting sewer gravity and pressurized pipeline conditions were divided into three main categories, namely, physical, environmental, and operational as shown in Figure 4.2. The physical factors included sewer pipeline characteristics such as: age, material type, size, buried depth, coating conditions and installation quality. The operational factors included: flow rate, infiltration and inflow, blockages, corrosive impurities and maintenance strategies in addition to the operating pressure for pipelines under pressure. Finally, the environmental factors included: bedding conditions, location, groundwater level and ground disturbance. Table 4-1 provides a detailed description and definitions for each of the studied factors.

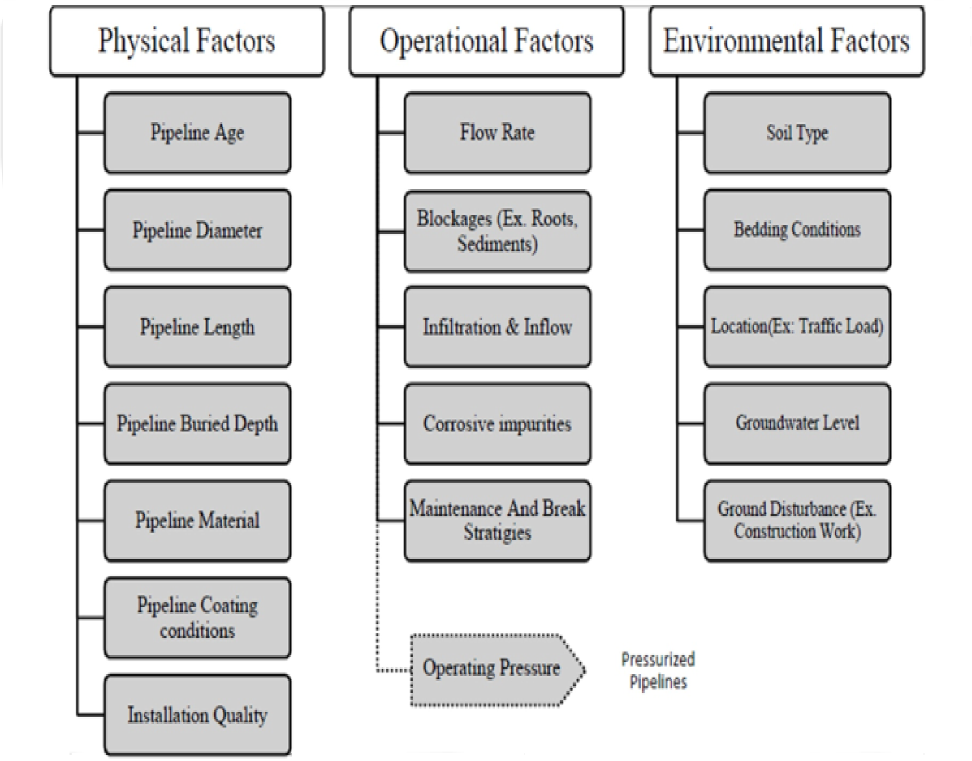


Figure 4-2: Classification of Factors Affecting Sewage Pipelines Condition

Table 4-1: Factors Affecting Sewer Pipeline Condition.

Main Factors	Sub-Factors	Description
Physical (PF)	**Age (AG)**	Effects of pipeline degradation become more significant over time.
	Diameter (DI)	The larger the pipe line diameter, the larger is its thickness, the lower is its deterioration rate and vice versa.
	Length (LE)	Longer pipes are more likely to suffer from bending stresses.
	Buried Depth (D)	Life loads impact increases at shallow depths and the soil overburden impact increases at high depths. Moderate depths increase the life of sewers
	Material (MT)	Different pipeline material show different failure patterns.
	Coating Conditions (CC)	Pipelines with good coating conditions have higher resistance against corrosion.
	Installation Quality (IQ)	Pipeline installation should be done according to certain standards and qualifications. High deterioration rates result from poor installation quality.
Operational (OF)	**Flow Rate (FR)**	Low flow rates causes deposition and accumulation of sediments while high flow rates causes corrosion for the piper's internal walls and causes disturbances specifically when moving between pipes having different diameters.
	Blockages (B)	Accumulation of deposits and sediments, intrusion of trees roots and other types of blockages have a significant effect on the structural and operational condition of a sewer pipeline.
	Infiltration and Inflow (II)	Infiltration washes soil particles and reduces the support along a pipeline.
	Corrosive Impurities (CI)	Sewage water carries substances and chemicals (for example: micro-bio species and slats) which impacts the water quality. In addition, these impurities can cause corrosion to the internal pipes' internal surfaces.
	Maintenance and break Strategies (MS)	The service life of sewer pipelines is increased by a good maintenance and break strategies.
	Operating Pressure (OP)	High pressures resulting in the distribution systems can lead to system fatigue, pump and device failure, or pipe ruptures.
Environmental (EF)	**Soil Type (ST)**	The soil which contacts the pipe surface directly has an impact on the deterioration process. Soils have different physical and chemical properties which have different impacts on the pipeline. For example, certain soils responds to moisture changes differently in respect to volume changes which applies loading on the pipe while others are highly corrosive.
	Bedding Conditions (BC)	Sewer pipeline failure chances increases with improper bedding conditions.
	Location (LO)	The location of the pipeline has an impact on the deterioration process. A pipeline can be installed in industrial area, residential area, schools, etc. Pipelines located in industrial areas or cities are subjected to different conditions that the pipelines located in residential areas. For example: city pipelines are exposed to heavier traffic loading. In addition, pipelines can be located beneath different surfaces (e.g. asphalt, walkway, unpaved, etc.).
	Groundwater Level (GW)	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.
	Ground Disturbance (GD)	Pipelines existing near a disturbed ground are subjected to high stresses and might have a sudden collapse.

4.3 Questionnaires

Open-ended (unstructured) questionnaires were additionally prepared to allow respondents to include additional factors that may have an impact on sewer pipelines condition. The questionnaires were distributed among different disciplines to capture the differences among the experts knowledge on the factors affecting the condition of sewer pipelines. Questionnaires were sent out to experts working in sewer field inspections and CCTV analysis, sewer designers, sewer site construction engineers and managers who have more than 30 years of experience in sewer maintenance and rehabilitation.

The used questionnaire provided a tool for interviewing experts and incorporating the elicited information into the developed models. The questionnaires were utilized: (1) to compare between main factors and sub-factors affecting sewer pipeline condition and (2) to determine the effect value of each factor on the pipeline condition. The questionnaires included an introductory part with a graphical representation of all the identified contributing factors, followed by two main sections. The first section sought the relative importance of factors and sub factors when compared to each other and how each factor would strongly affect the pipeline condition. The second section focused on the effect of the different factors on the condition of the pipeline.

4.3.1 Factor's Weights (Wi)

The importance of factors was calculated by conducting a pairwise comparison between the selected factors. The comparison can be categorized into three levels: (1) between the main factors with respect to the sewer pipeline condition; (2) between the sub-factors of each main factor; and (3) between the main-factors with respect to each other. The pairwise comparison of each level was designed to reflect the opinion of the experts on the degree of importance for each factor over the other(s), with respect to the goal under consideration. The degree of importance was scaled from 1 to 9 according to Saaty's nine points scale (Saaty, 1996) with"1" indicating no significant influence of a factor over the other(s), while "9" indicating that there is an absolute influence. In Table 4-2 an example for how pairwise comparison was carried out based on Saaty's scale in an ANP network is shown. For instance, if the respondent sees that the "Diameter" has a very strong influence over the "Age" with respect to "physical factors", they could check the suitable box that reflects the degree of influence(i.e.: a value of 7 corresponding to very strong would be assigned in the pairwise comparison). The same method is then repeated for the rest of the physical factors and on the different levels of the developed network.

4.3.2 Factor's Effect Values

Sub-factors can have different characteristics having different effect values on the condition of sewer pipeline. For instance, the "age" sub-factor has characteristics that range in value. These ranges were identified based on meetings with experts were a pipeline is considered new, medium or old if the age ranges from (0-15), (15-30) or >30, respectively and similarly for the rest of the sub-factors. The expert was requested to use a scale from 0 to 10 in this section of the questionnaire in which a value of "0" indicates the worst effect and "10" indicates the best effect on the pipeline condition for each sub-factor characteristic. Table 4-3 shows a sample for this part of the questionnaire. A full copy of the questionnaire can be found in appendix A.

Table 4-2: Questionnaire Sample for relative importance used in Pairwise Comparison for Main factors and Sub-Factors in gravity and pressurized pipelines

	←			**Degree Of Importance**				→	
Criterion (X)	**(9)** Absolute	**(7)** Very Strong	**(5)** Strong	**(3)** Moderate	**(1)** Equal	**(3)** Moderate	**(5)** Strong	**(7)** Very Strong	**(9)** Absolute	**Criterion (Y)**
1- Main Factors with respect to Sewer Pipeline Condition										
Sewer Pipelines Condition										
Physical Factors				✓						Environmental Factors
							✓			Operational Factors
2- Sub-Factors With Respect to Each Other										
Physical Factors										
Pipeline Age								✓		Pipeline Diameter
		✓								Pipeline Length
								✓		Pipeline Buried Depth
							✓			Pipeline Material
						✓				Pipeline Coating Conditions
									✓	Installation Quality
Operational Factors										
Corrosive Impurities								✓		Blockages (Ex. Roots, Sediments)
							✓			Infiltration & Inflow
								✓		Flow Rate
								✓		Maintenance And Break Record
Environmental Factors										
Groundwater Level							✓			Soil Type
									✓	Bedding Conditions
								✓		Location (Ex. Traffic Load)
								✓		Ground Disturbance (Ex. Construction Work)
3- Main Factors With Each Other										
Physical Factors										
Environmental Factors							✓			Operational Factors
Environmental Factors										
Physical Factors							✓			Operational Factors
Operational Factors										
Physical Factors				✓						Environmental Factors

Table 4-3: Questionnaire Sample for effect values of different factors for gravity and pressurized pipelines

Main Factor	Sub-factors	Unit Of Measure	Qualitative Description (Parameters)	Effect Value On Sewer Gravity Pipelines (0 – 10)	Effect Value On Sewer Pressurized Pipelines (0 – 10)
Physical	Pipeline Age	(Years)	Old (>30)	8	9
			Medium (15-30)	6	8
			New (<15)	4	6
	Pipeline Diameter	(m)	Small (<300)	8	5
			Medium (300-600)	6	5
			Large (>600)	4	6
			:		
	Installation Quality	(%)	Poor	10	10
			Fair	7	8
			Good	4	5
Operational	Flow Rate	(m^3/d)	Low	2	3
			Medium	3	4
			High	6	7
			:		
	Maintenance And Break Strategies	(%)	Poor	8	10
			Fair	5	7
			Good	1	3
Environmental	Soil	Type	Rock	3	3
			Sand	5	5
			:		
	Ground Disturbance	(%)	Low	3	3
			Moderate	5	5
			High	8	8

4.3.3 Responses

Forty questionnaires were received out of the sixty that were distributed. Four questionnaires where further eliminated because they were considered as outliers and 36 responses were considered in developing the condition assessment model. The considered questionnaires' responses showed coherent and minimum variation values in which all the respondents agreed that the included factors in the questionnaires covered all possible aspects that might influence the condition of gravity and pressurized sewer pipelines.

4.4 Validation Set

In order to validate the proposed model a dataset collected from the Drainage Networks Operations and Maintenance Department in Ashghal Public Work Authority, Doha, Qatar was used. The validation set included actual conditions for 549 gravity pipelines with 6 available factors which are: age, diameter, length, and buried depth, pipeline position relative to groundwater and pipeline material. The actual condition was based on a CCTV analysis following a condition code EN13508 (British Standards Institution (BSI), 2012), Class model EUROdss and class method DWA-M 149-3 (German Association for Water, Wastewater and Waste (DWA), 2015).

CHAPTER 5: MODELS DEVELOPMENT AND IMPLEMENTATION

5.1 Factors' Weight (*Wi*) Determination

The factor's Weight (Wi) for both approaches were calculated as illustrated below.

5.1.1 Fuzzy Analytic Network Process (FANP)

Analytical network process (ANP) is considered as a multi-criteria decision analysis technique that takes into consideration interdependencies between decision alternatives. However, ANP neglects uncertainties of human judgment when evaluating the pairwise comparison between the different factors. Therefore FANP was used to account for interdependency between different factors and the uncertainties and vagueness accompanied by human judgments. ANP was used to model a three level network representing all contributing factors and sub-factors to determine how strongly each of them affect sewer pipeline conditions. Fuzzy Preference Programming method was used to conduct FANP (Zhou, 2012). Relative weights are determined as a solution for a nonlinear maximization problem where, the constraints are the upper and lower fuzzy numbers and the global weights are the objective of the problem.

In the conventional ANP models, pairwise comparisons are performed on the element and cluster levels. Relative weights are determined from pairwise comparison, then are put into a matrix which is called super-matrix. The super-matrix represents the interrelationships of elements on different levels. Table 4-2 shows a general arrangement of a super-matrix in a conventional ANP technique, Where C_N represents the N^{th} cluster, and E_{Nn} represents the n^{th} element in the N^{th} cluster (Piantanakulchai, 2005). W_{ij} sub-matrix consists of the collection of the priority weight vectors (w) of the elements in the i^{th} cluster with respect to the j^{th} cluster. The weights obtained from the pairwise comparison on the cluster level forms an eigenvector, with a summation of unity. In order to obtain global priority vector, the weighted super-matrix is raised to a limiting power as per Equation (25).

$$\lim_{x \to \infty} E^k \tag{25}$$

Table 5-1: General Arrangement of Analytical Network Process (ANP) Super-matrix

		C_1	C_2	---	C_N
		E_{11} E_{12} --- E_{1n}	E_{21} E_{22} --- E_{2n}		E_{N1} E_{N2} --- E_{Nn}
C_1	E_{11} E_{12} --- E_{1n}	W_{11}	W_{12}	---	W_{1N}
C_2	E_{21} E_{22} --- E_{2n}	W_{21}	W_{22}	---	W_{2N}
⁞		⁞	⁞	⁞	⁞
C_N	E_{N1} E_{N2} --- E_{Nn}	W_{N1}	W_{N2}	---	W_{NN}

In this study, fuzzy preference programming (FPP) method was used to determine the consistency ratios of fuzzy pairwise comparison matrices and local weights by formulating a nonlinear prioritization problem (Mikhailov, 2004).

In the fuzzy preference programming method, the objective is to maximize the consistency ratio which is a function in weights. The formulated non-linear maximization problem is shown in Equation 26 (Zhou, 2012).

$$\left.\begin{array}{l} \text{Max } \lambda \text{ Such that,} \\ (m_{ij} - l_{ij})\lambda\omega_{ij} - \omega_i + l_{ij}\omega_j \leq 0 \\ (u_{ij} - m_{ij})\lambda\omega_{ij} + \omega_i - u_{ij}\omega_j \leq 0 \\ \sum_{k=1}^{n} \omega_k = 1, \omega_k > 0, \\ k = 1,2,3,\ldots,n,\ i = 1,2,3,\ldots,n\text{-}1 \text{ and } j = 2,3,\ldots,n,\ j > i \end{array}\right\} \qquad (26)$$

Where, l_{ij}, m_{ij}, u_{ij} are lower, middle and upper bounds of the triangular fuzzy number used in pairwise comparison and ω_k is priority crisp vector in which relative weights are present.

During the process of collecting data for the relative importance of the different factors, experts specify their preferences in a linguistic way. The fuzzy linguistic variable should reflect different aspects of human language (Zhou, 2012). In this study a scale consisting of five terms which accounts for fuzziness was chosen. The scale adds and subtracts “0.5” from every response of the pairwise comparison to construct the upper and lower matrices. Table 5-2 shows a sample for the developed matrices using the adjusted scale in a gravity pipeline. Non-Linear FPP Solver was developed based on the Optimization Toolbox of MATLAB, where solutions for “crisp priorities’ weights” were derived without requiring the conventional defuzzification procedure performed in the ordinary FANP technique.

Figure 5-1 shows the steps for the conduction of the FANP process. The Figure shows the different steps for constructing un-weighted and weighted super-matrices and the limit matrix required for getting the final weights. Table 5-3 shows the constructed three matrices for the different affecting sub-factors.

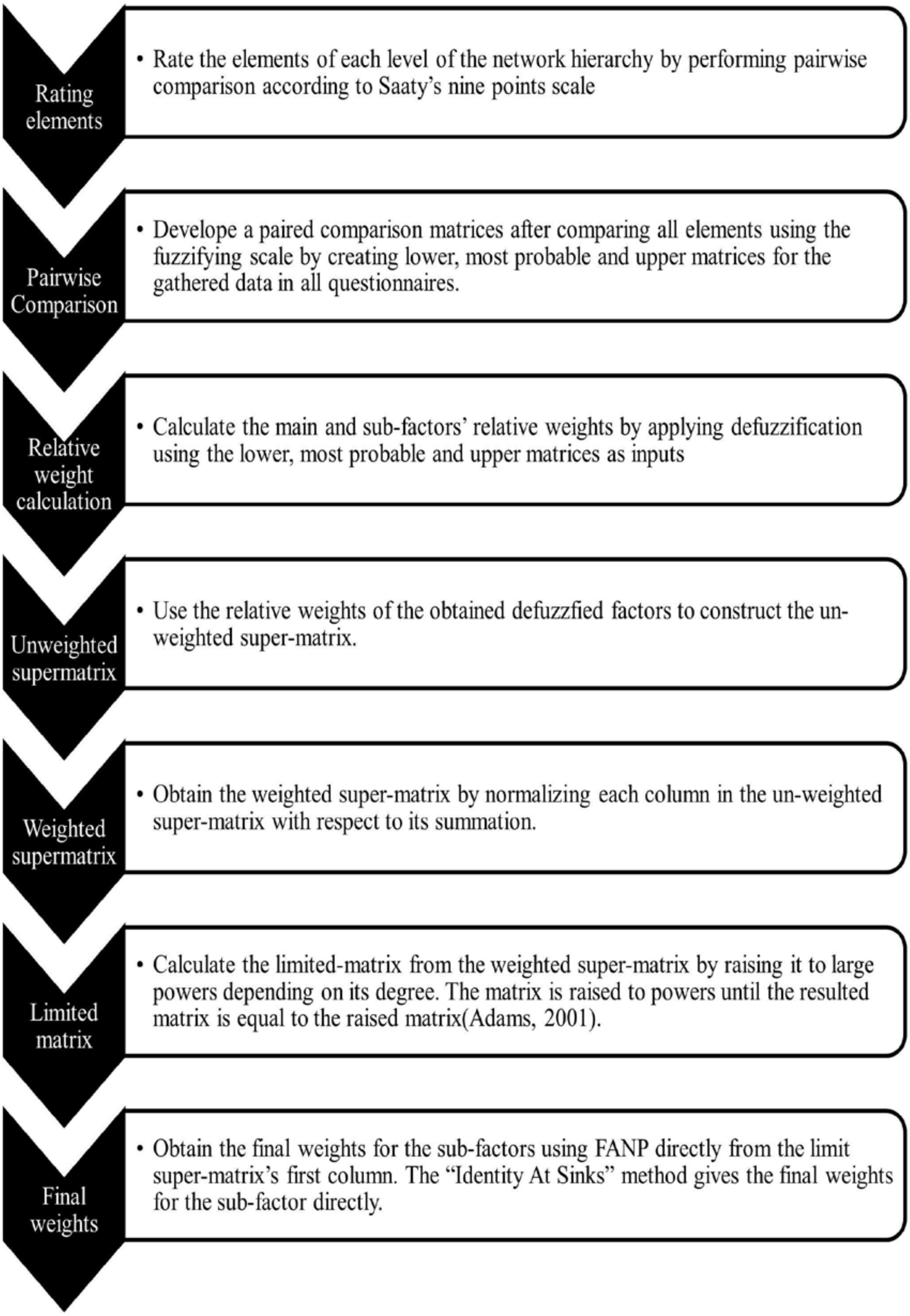


Figure 5-1: Steps for Conducting FANP

Table 5-2: Sample of Pairwise Comparison Matrices in Gravity Pipelines

Factors	Lower Limit Matrix*					Most Probable Matrix*					Upper Limit Matrix*				
	Groundwater level	Soil Type	Bedding Conditions	Location	Ground Disturbance	Groundwater level	Soil Type	Bedding Conditions	Location	Ground Disturbance	Groundwater level	Soil Type	Bedding Conditions	Location	Ground Disturbance
Groundwater level	1	4 1/2	4 1/2	1/7.5	1/7.5	1	5	5	1/7	1/7	1 1/2	5 1/2	5 1/2	1/6.5	1/6.5
Soil Type	1/5.5	1	1	1/9	1/9	1/5	1	1	1/9	1/9	1/4.5	1 1/2	1 1/2	1/8.5	1/8.5
Bedding Conditions	1/5.5	1	1	1/9	1/9	1/5	1	1	1/9	1/9	1/4.5	1 1/2	1 1/2	1/8.5	1/8.5
Location	6 1/2	8 1/2	8 1/2	1	1	7	9	9	1	1	7 1/2	9	9	1 1/2	1 1/2
Ground Disturbance	6 1/2	8 1/2	1/9	1	1	7	9	1/9	1	1	7 1/2	9	1/8.5	1 1/2	1 1/2

*Lower, Most probable and upper limit matrices values are as per the adjusted Triangular Fuzzy Number (TFN) matrix:

$$\begin{bmatrix} (1,1,1\frac{1}{2}) \\ (2\frac{1}{2},3,3\frac{1}{2}) \\ (4\frac{1}{2},5,5\frac{1}{2}) \\ \left(6\frac{1}{2},7,7\frac{1}{2}\right) \\ (8\frac{1}{2},9,9) \end{bmatrix}$$

Table 5-3: Un-weighted Super-matrix, Weighted Super-matrix and Limit Super-matrix for different affecting factors

Fac.	Un-weighted Super-matrix				Weighted Super-matrix				Limit Super-matrix			
	NC	PF	…	GD	NC	PF	…	GD	NC	PF	…	GD
NC	0.000	0.000	…	0.000	0.000	0.000	…	0.000	0.000	0.000	…	0.000
PF	0.333	0.000	…	0.000	0.333	0.000	…	0.000	0.000	0.000	…	0.000
OF	0.333	0.167	…	0.000	0.333	0.083	…	0.000	0.000	0.000	…	0.000
EF	0.333	0.833	…	0.000	0.333	0.417	…	0.000	0.000	0.000	…	0.000
AG	0.000	0.037	…	0.000	0.000	0.018	…	0.000	0.008	0.020	…	0.000
DI	0.000	0.037	…	0.000	0.000	0.018	…	0.000	0.008	0.020	…	0.000
LE	0.000	0.037	…	0.000	0.000	0.018	…	0.000	0.008	0.020	…	0.000
D	0.000	0.223	…	0.000	0.000	0.111	…	0.000	0.051	0.120	…	0.000
MT	0.000	0.223	…	0.000	0.000	0.111	…	0.000	0.051	0.120	…	0.000
CC	0.000	0.223	…	0.000	0.000	0.111	…	0.000	0.051	0.120	…	0.000
IQ	0.000	0.223	…	0.000	0.000	0.111	…	0.000	0.051	0.120	…	0.000
FR	0.000	0.000	…	0.000	0.000	0.000	…	0.000	0.090	0.042	…	0.000
B	0.000	0.000	…	0.000	0.000	0.000	…	0.000	0.024	0.011	…	0.000
II	0.000	0.000	…	0.000	0.000	0.000	…	0.000	0.024	0.011	…	0.000
CI	0.000	0.000	…	0.000	0.000	0.000	…	0.000	0.022	0.010	…	0.000
MS	0.000	0.000	…	0.000	0.000	0.000	…	0.000	0.197	0.092	…	0.000
ST	0.000	0.000	…	0.000	0.000	0.000	…	0.000	0.036	0.026	…	0.000
BC	0.000	0.000	…	0.000	0.000	0.000	…	0.000	0.019	0.013	…	0.000
SR	0.000	0.000	…	0.000	0.000	0.000	…	0.000	0.019	0.013	…	0.000
LO	0.000	0.000	…	0.000	0.000	0.000	…	0.000	0.169	0.121	…	0.000
GD	0.000	0.000	…	1.000	0.000	0.000	…	1.000	0.169	0.121	…	1.000

5.1.2 Monte-Carlo Simulation

Based on the collected 36 questionnaires' (i.e. responses), there were different weights for each factor, these weights were fed into Monte-Carlo simulation to develop probability distribution curves. Monte-Carlo simulation has the ability to randomly select values in a certain distribution translating it into another distribution based on the most frequently occurred values. Monte-Carlo simulation computes the most probable weight based on the repeated random sample collection and statistical analysis (Raychaudhuri, 2008). The simulation procedure involves two operations, which are: "sampling" and "running iterations" (Salem, et.al, 2003). In the sampling operation, the input parameters values are obtained randomly based on the probabilistic distributions. In the running iterations, results from the model are calculated based on the input parameters. In each iteration, one sample is drawn from each input probability distribution. When last iteration is reached, the single-valued output results are aggregated to produce one output distribution. Monte-Carlo simulation result in an output distribution that represents the most probable value for the factors' weights' based on the input parameters eliminating the uncertainties due to the different values for these weights.

The statistical data of the resulted probability distributions of the final weights corresponding to each individual factor is summarized in Table 5-4 for sewer gravity and pressurized pipelines. To test goodness of actual frequencies from sampled data and frequencies from theoretical distributions, Chi-Squared (Ch-Sq), Anderson-Darling (A-D), and Kolmogorov-Smirnov (K-S) tests were the selected statistical tests from the several available tests.

Table 5-4: Summary of Statistical Analysis Results for Factor Weights

Network Type	Main Factor	Sub-Factor	Distribution	Mean Final Weight (μ)	A-D Test		K-S Test		Chi-Sq Test	
					Test Value	P-Value	Test Value	P-Value	Test Value	P-Value
Gravity	PF	AG	Lognormal	0.035	0.364	0.327	0.107	0.259	8.722	0.033
		⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
		IQ	Logistic	0.075	0.778	0.022	0.130	0.054	10.667	0.031
	OF	FR	Lognormal	0.048	0.519	0.107	0.119	0.144	2.889	0.409
		⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
		MS	Weibull	0.075	0.885	0.052	0.147	0.083	7.167	0.067
	EF	ST	Lognormal	0.039	0.197	0.872	0.091	0.601	1.722	0.632
		⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
		GD	Logistic	0.107	0.482	0.172	0.130	0.056	8.333	0.080
Pressure	PF	AG	Lognormal	0.040	0.309	0.460	0.123	0.103	6.389	0.094
		⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
		IQ	Normal	0.078	0.189	0.896	0.080	0.835	1.722	0.787
	OF	FR	Lognormal	0.038	0.206	0.788	0.080	0.759	2.889	0.409
		⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
		MS	Weibull	0.067	0.493	0.389	0.088	0.872	4.444	0.217
	EF	ST	Lognormal	0.032	0.198	0.831	0.074	0.840	6.389	0.094
		⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
		GD	Normal	0.088	0.346	0.475	0.091	0.670	1.333	0.856

The best probability fit was chosen based on the maximum P-value of the three tests. The P-value indicates that for a null hypothesis (i.e.: no difference between the actual and theoretical distributions), the observed difference is equal to the P-value due to random sampling error. This means that for P-values approaching 0, the corresponding distribution best represents the resulting distribution. The mean value for the final weights probability distribution for gravity and pressurized pipelines are shown in Figure 5-2.

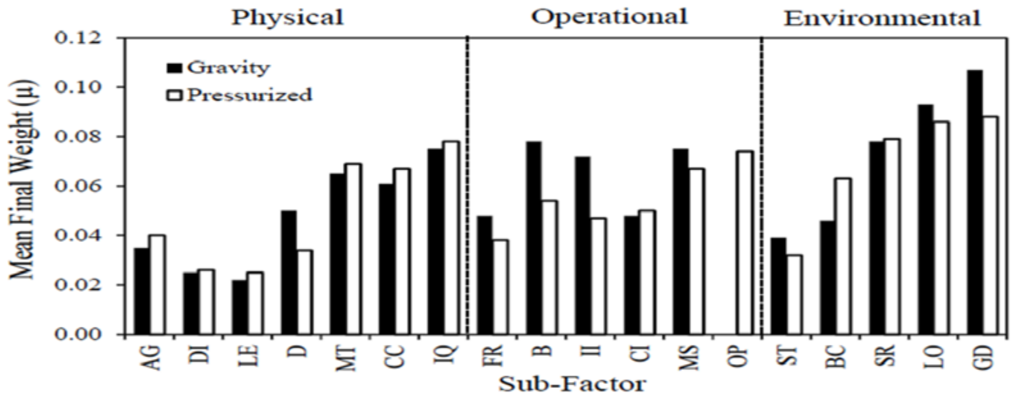


Figure 5-2: Factors' final weights calculated using FANP and Monte-Carlo simulation for Gravity and Pressurized Pipelines

5.2 Effect Value

5.2.1 First Approach (Condition Curves)

The same technique described in Section 5.1.2 was applied for the different effect values of each factor as shown in Table 5-5 for sewer gravity pipelines and Table 5-6 for sewer pressurized pipelines.

Table 5-5: Summary of Statistical Analysis Results for Factor Effect Values in Gravity Pipelines

Main Fac.	Fac.	Characteristic	Distr.	Mean Effect Value (μ)	A-D Test		K-S Test		Chi-Sq Test	
					Test Value	P-Value	Test Value	P- Value	Test Value	P- Value
PF	AG	Old >30	Max. extr.	2.780	0.565	0.147	0.172	0.024	3.897	0.273
		Medium (15-30)	Gamma	5.530	1.117	0.022	0.227	0.000	10.93	0.004
		New <15	Logistic	8.590	1.535	0.000	0.223	0.000	25.00	0.000
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	IQ	Poor <30%	Max. extr.	1.980	0.736	0.052	0.148	0.102	3.069	0.381
		Fair (30-70)%	Normal	5.190	0.787	0.035	0.181	0.017	9.690	0.021
		Good >70%	Weibull	8.520	0.976	0.122	0.159	0.182	12.58	0.002
OF	FR	Low <30%	Logistic	4.700	0.466	0.191	0.155	0.025	1.414	0.702
		Medium (30-70)%	Weibull	8.120	1.800	0.036	0.265	0.000	27.07	0.000
		High >70%	Weibull	4.900	0.597	0.241	0.133	0.312	3.90	0.143
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	MS	Poor <30%	Max. extr.	2.760	0.516	0.194	0.124	0.309	2.241	0.524
		Fair (30-70)%	Weibull	5.740	0.877	0.071	0.174	0.087	12.17	0.002
		Good >70%	BetaPERT	8.660	1.264	---	0.210	---	19.62	0.000
EF	ST	Rock <50%	Uniform	5.750	0.648	0.474	0.148	0.444	3.483	0.323
		Sand (50-100)%	Normal	6.280	0.429	0.305	0.142	0.145	1.414	0.702
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	GD	Low (0-30)%	Weibull	8.160	0.681	0.149	0.148	0.155	11.76	0.003
		Medium (30-70)%	Max. extr.	5.560	1.366	0.000	0.223	0.000	17.14	0.001
		High (70-100)%	Normal	2.620	0.749	0.045	0.176	0.023	25.00	0.000

Table 5-6: Summary of Statistical Analysis Results for Factor Effect Values in Pressurized Pipelines

Main Fac.	Fac.	Characteristic	Distr.	Mean Effect Value (µ)	A-D Test		K-S Test		Chi-Sq Test	
					Test Value	P-Value	Test Value	P- Value	Test Value	P- Value
PF	AG	Old >30	Gamma	2.300	0.517	0.282	0.131	0.365	2.000	0.368
		Medium (15-30)	Weibull	5.230	1.007	0.059	0.219	0.029	14.00	0.001
		New <15	Weibull	8.560	2.184	0.000	0.243	0.000	34.40	0.000
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	IQ	Poor <30%	Normal	1.600	0.790	0.035	0.142	0.128	6.400	0.094
		Fair (30-70)%	Weibull	5.060	1.652	0.031	0.232	0.025	24.80	0.000
		Good >70%	Uniform	8.500	1.860	0.062	0.243	0.033	34.80	0.000
OF	FR	Low <30%	Uniform	4.750	1.009	0.244	0.186	0.179	6.800	0.079
		Medium (30-70)%	Weibull	8.280	1.296	0.045	0.228	0.029	18.00	0.000
		High >70%	Min extr.	4.930	0.862	0.025	0.148	0.087	3.200	0.362
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	MS	Poor <30%	Normal	2.130	0.639	0.089	0.136	0.178	14.00	0.003
		Fair (30-70)%	Normal	5.420	0.898	0.019	0.194	0.000	12.40	0.006
		Good >70%	Weibull	8.670	1.758	0.000	0.230	0.000	28.40	0.000
EF	ST	Rock <50%	Max extr.	5.890	0.783	0.039	0.154	0.061	2.400	0.494
		Sand (50-100)%	Uniform	6.000	0.712	0.425	0.183	0.196	18.40	0.000
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	GD	Low (0-30)%	Weibull	8.500	0.830	0.160	0.171	0.123	10.80	0.005
		Medium (30-70)%	Max extr.	5.710	1.160	0.000	0.168	0.027	9.200	0.027
		High (70-100)%	BetaPERT	2.500	1.281	0.000	0.210	0.000	24.00	0.000

The effect value of the factors on the pipeline's condition generated from Monte-Carlo simulation does not vary with age. Based on experts' opinion, the impact of the same factor should vary with age. For example, smaller diameter pipelines deteriorate faster than bigger diameter pipelines, but the effect of the diameter factor on the pipeline's condition differs significantly with time. As a result and to account for the change of the effect value during the lifetime of pipelines, age dependent condition curves were developed. The condition curves were generated using the mean values resulting from the developed probability distributions for the different effect values as the base points for these curves. Equation 27 shows the formula by which the curves were plotted.

$$\mathrm{CI_t} = \mathrm{CI_0} - \left(\frac{\mathrm{CI_0} - \overline{\mathrm{X}}}{\mathrm{T}}\right) * \mathrm{CI_{t+1}} \qquad (27)$$

Where,

CI_0: is the initial condition of the pipe at time = 0, which is 10,

CI_t: is the condition index at time (t),

T is the overall time interval on which the curves are generated,

$\bar{X}$: is the mean effect value resulting from probability distributions and

CI_{t+1}: is the condition index at the successive time step.

An example of the generated curves for gravity pipeline diameter, length, buried depth and groundwater level condition index over different time periods is shown in Figure 5-3. The curves represent the condition index of the pipeline on the vertical axis, while the age is represented on the horizontal axis.

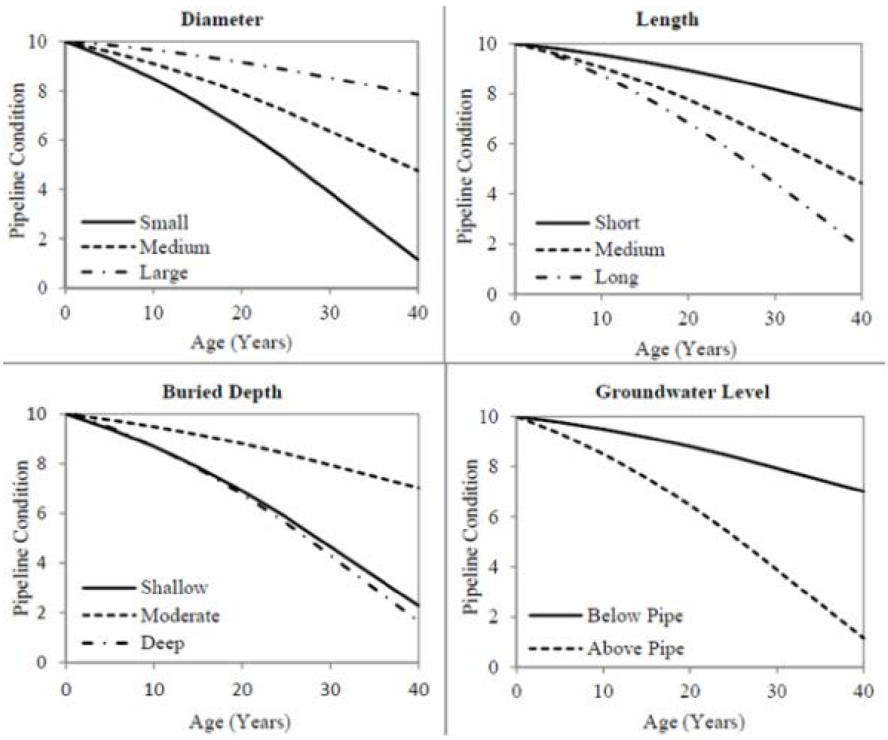


Figure 5-3: Pipeline Condition Curves for Different Sub-Factors over Age

5.2.2 Second Approach (Fuzzy Set Theory)

Fuzzy Set Theory (FST) is a mathematical model that was first introduced by Zadeh (1965), designed to generalize the concept of classical (or crisp) sets. FST attempts to provide a better tools to deal with vague situations that cannot be captured by the classical Set theory. The membership of a classical set can be considered as a function with only two possible values (i.e.: an element either belongs to certain set of elements or does not). The generalization made by Zadeh (1965) is to produce Fuzzy Sets that allows the membership function to have a gradual transition with any degree of membership from none to full. The significance of fuzzy variables is that they facilitate the gradual transition between states of a crisp variable and consequently, possess the capability to express and deal with uncertainties, unlike crisp variables that ignore. Fuzzy numbers "F" can be represented by a set [a_1, a_2, a_3, a_4]. Each fuzzy number defined by a membership function μ_F, which can be expressed by Equation 28.

$$\mu_F(x) = \begin{cases} 1 & , when\ a_2 < x < a_3 \\ 0 < value < 1 & , when \begin{cases} a_1 < x < a_2 \\ a_3 < x < a_4 \end{cases} \\ 0 & , Otherwise \end{cases} \quad (28)$$

Membership functions (MFs) are the building blocks of FST, in which the fuzziness in a fuzzy set is determined by its MF. Accordingly, the shapes of MFs are important for each particular problem. MFs may have different shapes like triangular, trapezoidal, Gaussian, etc. For triangular fuzzy numbers a_2 would have the same value of a_3. The only condition that a MF must satisfy is that it must vary between 0 and 1.

In order to determine the inputs to be used in the ER module, the questionnaires' responses were used to generate the linguistic factors' fuzzy thresholds for the effect values and their corresponding membership functions in similar manner to the FANP algorithm. The methodology of implementing the FST starts with defining the minimum average lower limit and maximum average upper limit for each linguistic factor affecting the pipeline conditions based on the questionnaires' responses. To represent the output for the effect of the different linguistic factors, a five grade fuzzy subset (Excellent, very good, good, fair and critical) is used. After determining the input and output thresholds values, a suitable membership function is chosen to represent the inputs and output. In this study, trapezoidal curves at extreme points and triangular curves for the intermediate points were used (Figure 5-4 to Figure 5-7). Triangular and trapezoidal fuzzy membership function shapes were used because they are suitable for representing linguistic variables (Lee, 1996). Membership functions have been divided into four zones 0 to 5 years, 5 to 15 years, 15 to 30 years and above

30 years in order to appropriately take into account the age effect on the developed model. In such way, better and reliable assessment for new pipelines is assigned over the older ones by taking into consideration the age influence on the pipelines deterioration. Figure 5-4 to Figure 5-7 show the plot of the generated membership functions for diameter, length and the buried depth for gravity pipelines and their corresponding shapes for the fuzzy thresholds. Similarly, membership functions were generated for the rest of the factors affecting gravity and pressurized pipelines. The figures were developed by fuzzifying the input to determine the MF, for which each factor belongs. The corresponding MF ($\mu_F(x)$) based on the five grade scale is calculated using Equation 28. Due to the uncertainty of the exact limits of the factors, the thresholds are overlapping at some intervals. Also, the trapezoidal shapes represent the extreme limits of excellent or critical membership functions for the thresholds, whereas triangular shapes are used to represent the three remaining membership functions in between the trapezoidal shapes.

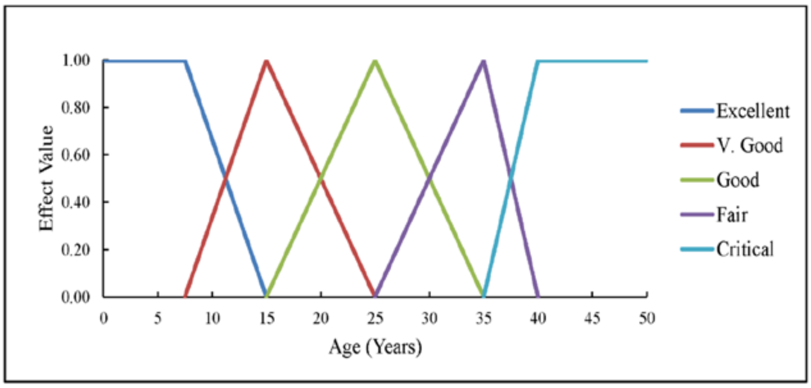


Figure 5-4: Membership Function for Pipelines’ Age Effect Value

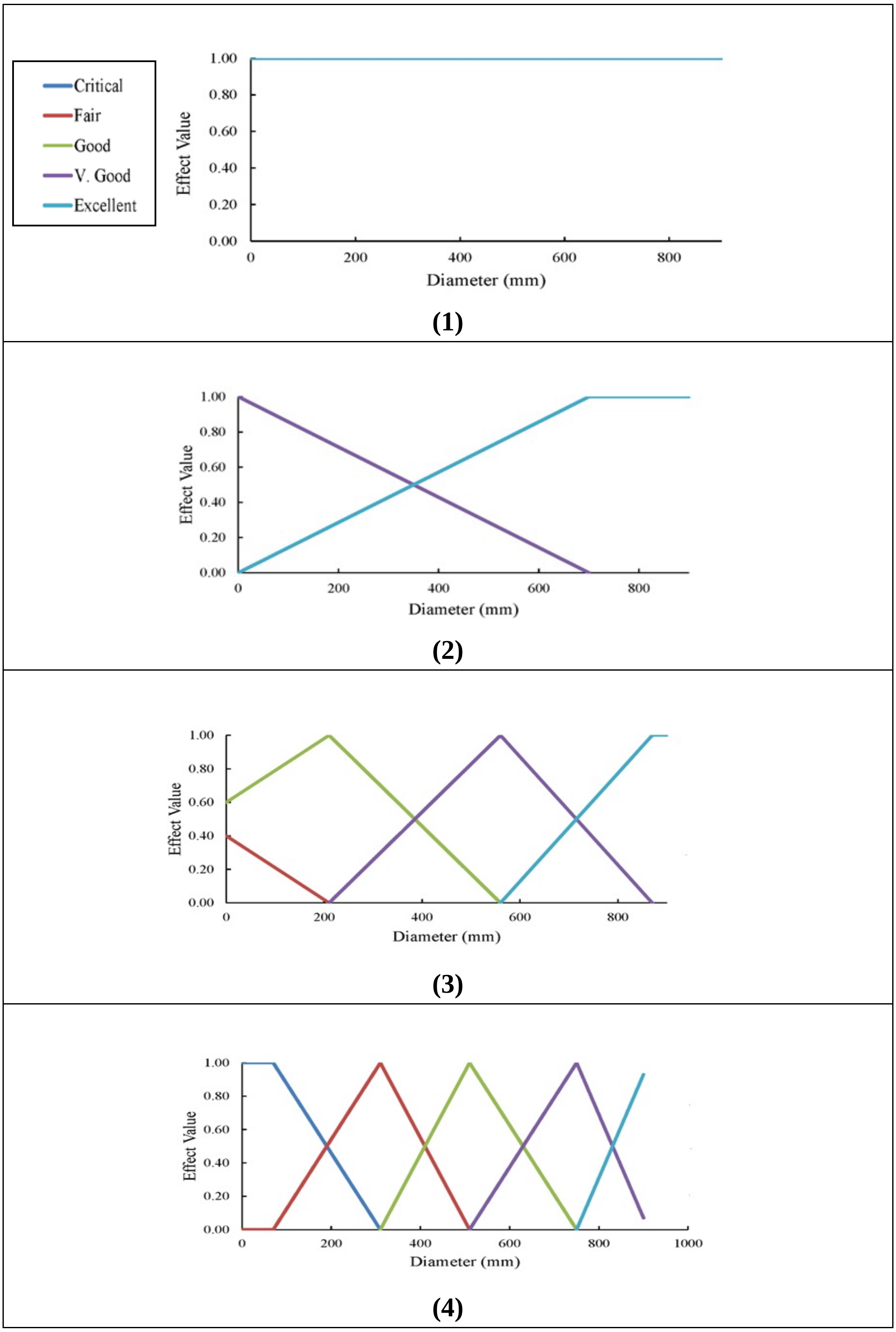


Figure 5-5: Membership Functions for Pipelines' Diameter Effect Values

1) Age 0 to 5 years, 2) Age 5 to 15 years, 3) Age of 15 to 30 years and 4) Age 30 to 40 years

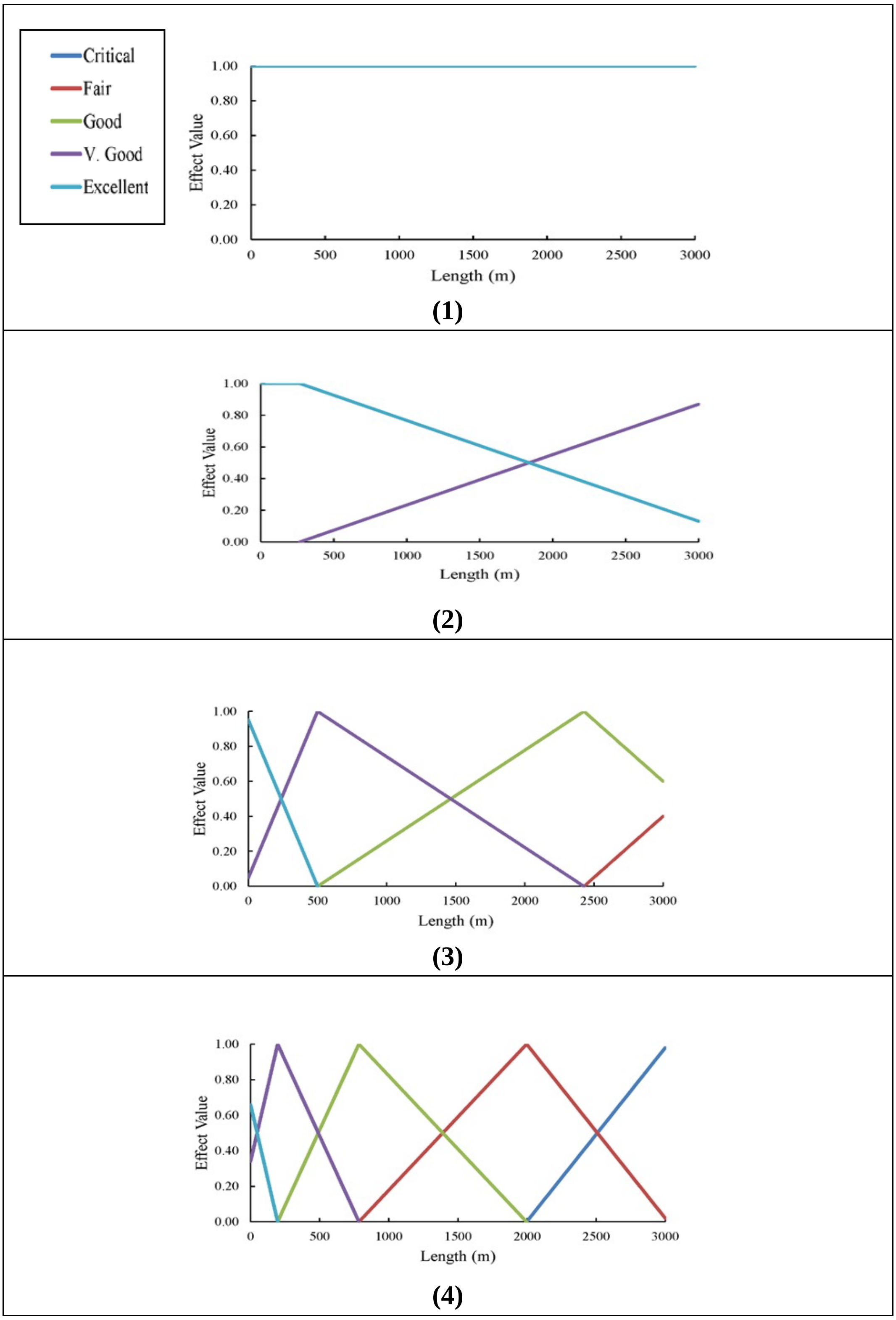


Figure 5-6: Membership Functions for Pipelines’ Length Effect Values

1) Age 0 to 5 years, 2) Age 5 to 15 years, 3) Age of 15 to 30 years and 4) Age 30 to 40 years

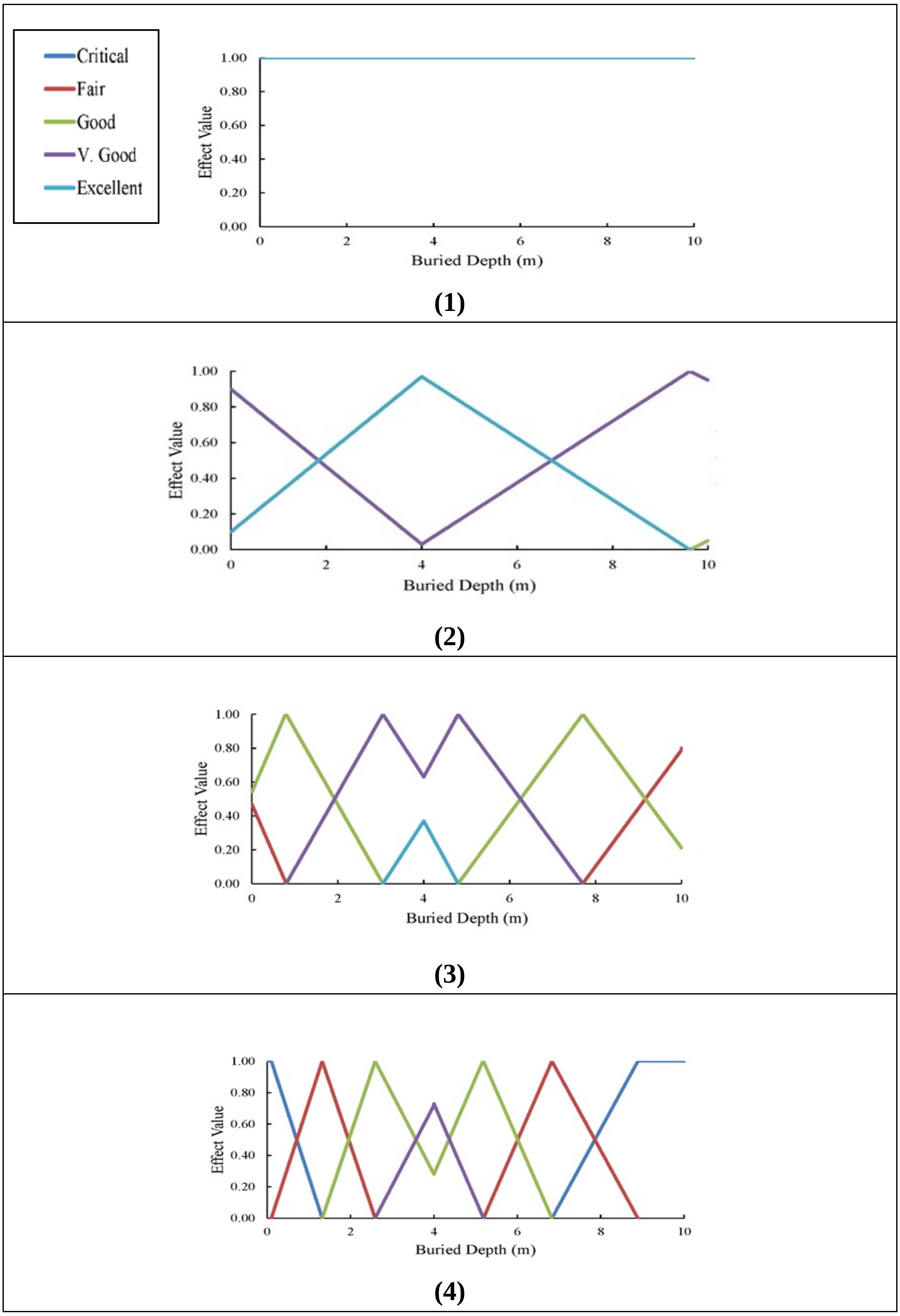


Figure 5-7: Membership Functions for Pipelines' Buried Depth Effect Value

1) Age 0 to 5 years, 2) Age 5 to 15 years, 3) Age of 15 to 30 years and 4) Age 30 to 40 years

5.3 Overall Condition Assessment Index

Equation (29) represents the overall condition assessment index model derived by simulation.

$$OCI_j = \sum_{i=1}^{k} W_i \ x \ EV_i \tag{29}$$

Where,

OCI_j is the overall condition index of sewer pipeline j,

EV_i is the effect value of factor i reflecting the factor score,

W_i is the final weight for factor I,

k is the number of factors.

The model provides the overall condition index assessing sewer pipelines, where a higher index indicates a better pipeline condition. The overall condition index and effect values of each factor ranges between the extreme values of 0 and 10; which shows that the pipeline is at its worst or best condition respectively.

5.3.1 First Approach (Monte-Carlo Simulation)

As shown in Equation (29), the model multiplies each pipeline's effect value obtained from the condition curves for each factor, by the probabilistic final weight of the corresponding factor. The results of these multiplications are added to calculate the mean overall condition index for each pipeline. The procedure is repeated for 1000 iterations (simulations) with stopping criterion parameters of 5% accuracy (ε = 0.05) and 99% confidence (α = 0.01). The sample variance based stopping rule used in this simulation (Bayer et al., 2014) is presented below in Equation 30.

Set n = 0, Generate $M_n$samples $(OCI_j)_{I=1}^{M_n}$ and compute sample variance

$(\overline{\sigma}_{M_n}^2)$

$$\overline{\sigma}_{M_n}^2 = \frac{1}{M_n - 1} \left(\sum_{I=1}^{M_n} (OCI_{j_I} - \overline{OCI}_{j_{M_n}}\right)^2 \quad (30)$$

While $2(1- f(\frac{\sqrt{M_n}\,\varepsilon}{\overline{\sigma}_{M_n}})) > \alpha$ do

Set $n = n+1$ and $M_n = 2M_{n-1}$

End while

Where,

I is the iteration number,

M_n is the number of samples,

$(OCI_j)_{I=1}^{M_n}$ is the overall condition for samples (M_n) and iteration (I),

$\overline{\sigma}_{M_n}^2$is the sample variance,

α is the confidence,

ε is the error,

$f(\frac{\sqrt{M_n}\,\varepsilon}{\overline{\sigma}_{M_n}})$ is the distribution function.

This reflects the strength of Monte-Carlo simulation in which a random final weight is chosen in each iteration based on the probability distribution determined for each factor. This randomness guarantees that the uncertainty is taken into consideration and the mean value of the *OCIj* obtained through the iterations is the final condition value for every pipeline. Based on the calculated condition value, the concerned authority can decide on the necessary actions to be taken for the pipeline, which is the purpose of this study. A sample of a probabilistic condition index output from Monte-Carlo simulation is shown in Figure 5-8.

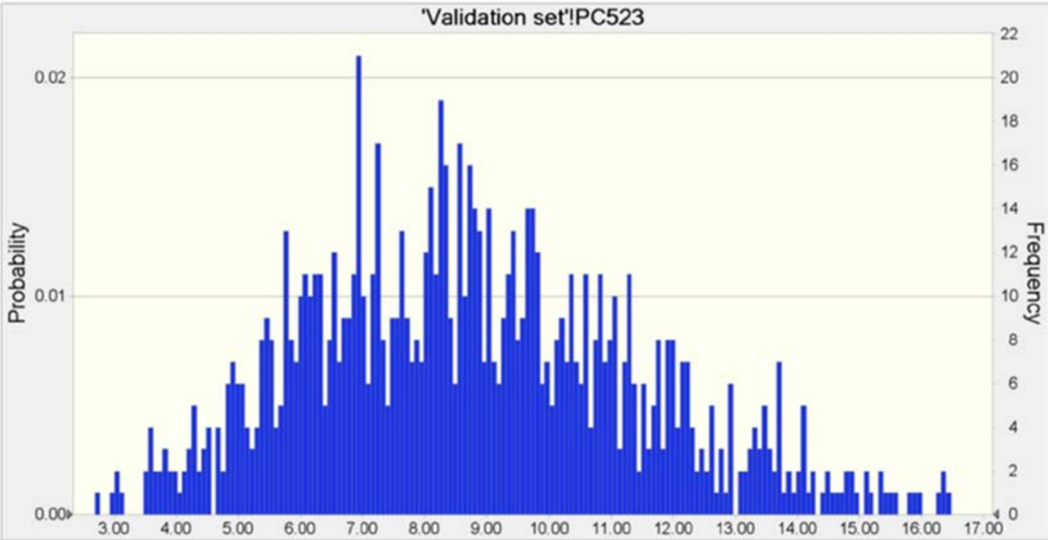


Figure 5-8: Sample of Monte-Carlo Simulation Output for Overall Condition Index Probability Distribution

5.3.2 Second Approach (Evidential Reasoning)

Evidential reasoning (ER) offers a rational methodology to deal with uncertainty, incompleteness and fuzziness for data aggregation. This approach was developed on the basis of decision theory and the Dempster-Shafer theory of evidence (Yang and Singh, 1994; Yang and Sen, 1994; Yang, 2001) to address Multi-Criteria Decision Making (MCDM) problems under uncertainty. ER methodology describes and handles various types of uncertainties by using the concept of the degrees of belief, in which each attribute of an alternative of a MCDM problem is described by a distributed assessment using a belief structure. Unlike conventional approaches that require scaling grades and averaging scores to aggregate attributes, the ER approach employs an evidential reasoning algorithm to aggregate belief degrees. The ER approach is a technique that allows aggregating many pieces of evidence (Yang and Xu, 2002). It aggregates two factors at a time and the resulting aggregation of the first two factors of evidence is aggregated with the third factor of evidence and so on.

The ER approach is used to determine the final condition index for sewer pipelines. The first steps in implementing the ER module is to identify the distinctive evaluation grades (H) that are represented by the linguistic variables (i.e. excellent, very good, good, fair, and critical) and to define the final weight (ωi) for each contributing factor. The belief structure of the formulated ER problem consists of degree of beliefs indicating the user's level of certainty about the condition of the pipeline (Excellent, very good,…etc.) based on the different contributing factors effect values. For instance the degree of belief is said to be high for an excellent pipeline condition for a new pipe with a low effect values of the contributing factors, while the degree of belief is considered low for very good pipeline conditions assuming an old pipeline with higher effect values for the contributing factors. After identifying the evaluation grades and relative weights, the degrees of belief are transformed into basic probability masses ($m_{n,i}$) using Equation 31, by multiplying the relative weights by the degrees of belief.

$$m_{n,i} = m_i(H_n) = \omega_i \beta_{n,i} \qquad n = 1, \dots, N;\ i = 1, \dots, L \qquad (31)$$

Where,

$m_{n,i}$ represents the degree to which the i^{th} basic attribute supports the hypothesis of attribute (y) (pipeline condition) to be assessed to the (n^{th}) grade (H_n).

($m_{H,i}$) is the remaining probability masses unassigned to any individual after all (N) grades have been considered for evaluating the general attribute. ($m_{H,i}$) is calculated as per equations 32, 33 and 34.

$$m_{H,i} = m_i(H) = 1 - \sum_{n=1}^{N} m_{n,i} - \omega_i \sum_{n=1}^{N} \beta_{n,i},\ i = 1,2,...,L \qquad (32)$$

$$\bar{m}_{H,i} = \bar{m}_i(H) = 1 - \omega_i, \qquad i = 1,2,...,L \qquad (33)$$

$$\tilde{m}_{H,i} = \tilde{m}_i(H) = \omega_i(1 - \sum_{n=1}^{N} \beta_i), \qquad i = 1,2,...,L \qquad (34)$$

Where,

$m_{H,i} = \bar{m}_{H,i} + \tilde{m}_{H,i}$ and $\sum_{i=1}^{L} \omega_i = 1$,

$\bar{m}_{H,i}$ is the remaining probability mass that has not been yet assigned to individual grades. While, $\tilde{m}_{H,i}$is the remaining probability mass unassigned to individual grades caused by the incompleteness of the assessment.

$m_{n,I(i)}$ and $m_{H,I(i)}$ can be calculated by aggregating the basic probability masses $m_{n,j}$and $m_{H,j}$for n = 1, … , N and J = 1, …. , i using Equations 35 to 37 which combines the two probability masses using normalizing factor $K_{I(i+1)}$.

The normalizing factor can be defined as $K_{I(i+1)} = \left[1 - \sum_{t=1}^{N} \sum_{j=1}^{N} m_{t,I(i)} m_{j,i+1}\right]^{-1}$

Where, $K_{I(i+1)}$is the normalizing factor so that the summation of $m_{n,I(i+1)} + m_{H,I(i+1)}$for n = 1, ..., N is 1.

$$m_{\ n,I(i+1)} = K_{I(i+1)}(m_{n,I(i)} m_{n,i+1} + m_{n,I(i)} m_{H,i+1} + m_{H,I(i)} m_{n,i+1}),\quad n = 1,2 ...,N \qquad (35)$$

Where, $m_{H,I(i)} = \bar{m}_{H,I(i)} + \tilde{m}_{H,I(i)}$

$$\bar{m}_{H,I(i+1)} = K_{I(i+1)}\left[\bar{m}_{H,I(i)} \bar{m}_{H,i+1}\right] \qquad (36)$$

$$\tilde{m}_{H,I(i+1)} = K_{I(i+1)}\left[\tilde{m}_{H,I(i)} \tilde{m}_{H,i+1} + \bar{m}_{H,I(i)} \tilde{m}_{H,i+1} + \tilde{m}_{H,I(i)} \bar{m}_{H,i+1}\right] \qquad (37)$$

By combining each two probability masses until all the factors are combined, the final probability masses can be converted into the final degrees of belief using Equations 38 and 39.

$$\beta_n = \frac{m_n}{1-\bar{m}_{H,I(L)}}, n = 1,2 \ldots,N \tag{38}$$

$$\beta_H = \frac{\tilde{m}_{H,I(L)}}{1-\bar{m}_{H,I(L)}} \tag{39}$$

Where,

$\beta_n$is the degrees of belief for the aggregated final assessment associated to the grades H_n and β_H represents the incompleteness of the overall assessment associated to H.

In order to determine the overall condition of the pipeline in the developed model, deffuzificaion is carried for the aggregated final assessment resulting from the ER module by utilizing the FST module. In the defuzzification process, the final degrees of belief are deffuzified into a crisp values. The deffuzification process is basically calculating the areas of the resulting figures for each MF, weighted average method was used to convert the fuzzy membership functions' overall condition into a crisp value.

5.4 Model Validation

In order to validate the proposed model a dataset collected from the Drainage Networks Operations and Maintenance Department in Ashghal Public Work Authority, Doha, Qatar was used as stated under Section 4.3.3. The validation set included actual conditions for 549 gravity pipelines with 6 available factors which are: age, diameter, length, and buried depth, pipeline position relative to groundwater and pipeline material. The pipeline material of the validation set obtained was

Vitrified Clay. Therefore, the pipeline material factor was disregarded and only the 5 remaining factors were considered in the validation process.

The condition varied from 1 to 5, where 1 indicates that the pipeline has minor defects and no action is required, while 5 indicates a pipeline with very heavy defects and an immediate action is required. The resulted predicted condition scale from the developed models has a scale that varies from 0 to 10.

In order to apply a valid comparison between the actual condition of a pipeline and the obtained condition from the models, two model calibrations were required. The first calibration was the conversion of the 0 -10 scale for the predicted pipes' condition to 1-5 scale for the actual pipes' condition. The thresholds of the calibrated scale are shown in Table 5-7. The conversion was basically done by anchoring the maximum and minimum of the two scales (0 anchored to 1 and 10 anchored to 5) and dividing the rest of the scale values into 5 classes.

Table 5-7: Conversion of Actual Condition Rating Scale to Model Prediction Condition Rating Scale

Actual Condition Scale	**Resulted Prediction Condition Scale**
5	0 to <3
4	3 to <5
3	5 to <7
2	7 to <9
1	9 to 10

The second calibration was converting the relative weights for the seventeen factors into an equivalent five factors' weights. Equation 40 was used to make this conversion in which the final obtained weights of the five factors included in the validation process were adjusted so that their summation would be equal to one.

$$w_{cal} = w_i + [\sum_{i=1}^{n} w_i * (1 - \sum_{i=1}^{n} w_i)] \tag{40}$$

Such that $\sum_{i=1}^{n} w_{cal} = 1$

Where,

w_{cal} is the calibrated factor's weight;

w_i is the original weight of the factor in case that the seventeen factors are present; n is the total number of factors in the problem (n=5 in the validation set).

Table10 includes a sample of the validation data set. For example, based on the characteristics of pipeline No.2 shown in Table 5-8, the resulted mean value from the developed model was 7.8 and accordingly the pipeline's predicted condition would be 2, while the actual CCTV condition gave a value of 1.

Table 5-8: Sample of Actual versus Predicted Model Condition Rating Values for Pipelines in Validation Dataset

Pipeline (No.)	Actual CCTV Condition	Mean Value	Predicted Model Condition
2	1	7.8	2
134	1	9.6	1
19	2	8.2	2
128	2	8.4	2
24	3	6.4	3
428	3	5.5	3
111	4	4.6	4
⋮	⋮	⋮	⋮

The developed model performance assessment was based on the mathematical diagnostics recommended in literature (Zayed and Halpin 2005; Al-Barqawi and Zayed 2006). In order to determine the model validity, Equations (41) and (42) were used which show the average validity percentage (AVP) and the average invalidity percentage (AIP), respectively. If the values of AIP are closer to 0 and AVP are closer to 100% the model is valid and vice versa. Likewise, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were used to validate the model using Equations (43) and (44), respectively. The model is considered sound if the values for MAE and RMSE are close to 0 (Dikmen et al. 2005). Finally, the fitness function equation (f_i) indicating that the developed model is valid if the calculated value using Equation (45) is close to 1000 and invalid when it is close to 0 (Dikmen et al. 2005).

$$\mathrm{AIP} = \left\{\sum_{i=1}^{n} \left|1 - \left(\frac{E_i}{C_i}\right)\right|\right\} \times \frac{100}{n} \tag{41}$$

$$\mathrm{AVP} = 100 - \mathrm{AIP} \tag{42}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |C_i - E_i|}{n} \tag{43}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (C_i - E_i)^2}{n}} \tag{44}$$

$$f_i = \frac{1000}{1 + \mathrm{MAE}} \tag{45}$$

Where,

AIP = Average Invalidity Percent;

AVP = Average Validity Percent;

MAE = Mean Absolute Error;

$RMSE$ = Root Mean Square Error;

f_i= fitness function;

E_i = predicted value;

C_i = actual value;

n = number of events.

Results obtained by the first approach were 15%, 85%, 0.12, 0.15, and 893 and by the second approach were 14%, 86%, 0.16, 0.11, and 898 for AIP, AVP, MAE, RMSE and f_i, respectively which are considered plausible results. The “actual versus predicted output plot” results for the developed model (Approach 1) are shown in Figure 5-9. In Figure 5-9, the condition indices resulting from the model for all the pipes from the validation set were grouped based on their categorical classes and compared to the actual condition rating. Figure 5-9 shows that the results from the developed model are very close to the actual ones indicating the soundness and accuracy of the proposed model. A comparison between the Actual Pipeline conditions and the predicted pipeline conditions for approaches 1 and 2 for each individual pipe is further presented in Figure 5-10.

Moreover, this model shows similar accuracy to previously developed models that used linear regression and back propagation neural networks techniques giving 85% and 86%, respectively (Chughtai and Zayed, 2008 and Khan et al., 2010). However, the enhancement in this model could be due to the fact that it neither required extensive data to create the model nor made strong assumptions that would result in higher condition rating values (Salman, 2010). On the other hand, a major portion of research addressing condition assessment models, only studied and analyzed the significance on pipelines' state without getting an index to express their conditions (Wirahadikusumah et al., 2001, Davies, 2001, Baur and Herz 2002, Younis and Knight, 2010). In these previous researches, limited factors varying between 4 and 10, such as pipe size, length, depth, material, type of waste, ground water level, street category, soil type and infiltration and how they contribute to sewer pipeline deterioration were studied, but little research studied the effect of factors such as coating conditions, maintenance and break strategies while taking into consideration the interdependencies between these contributing factors. Moreover, no research addressed these factors and their effect on the pressurized sewer pipelines (i.e. rising mains).

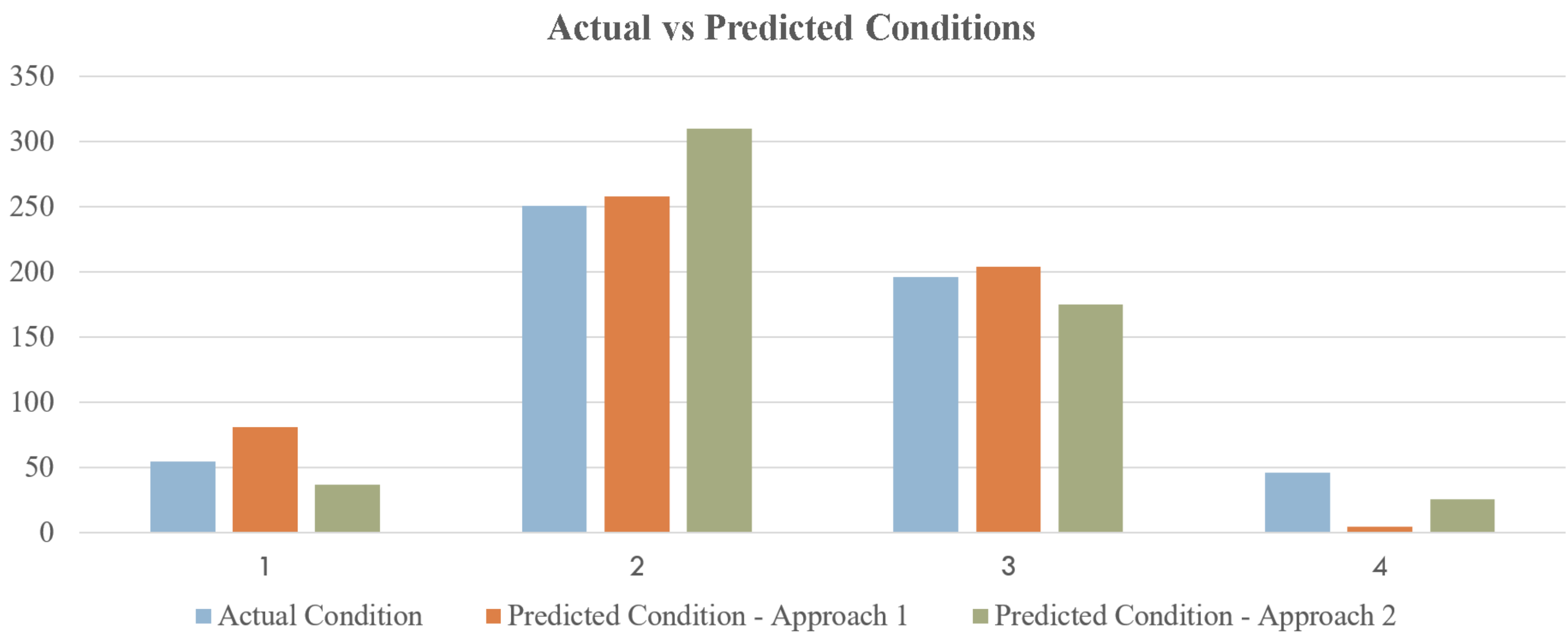


Figure 5-9: Actual Versus Predicted Overall Condition Index (1)

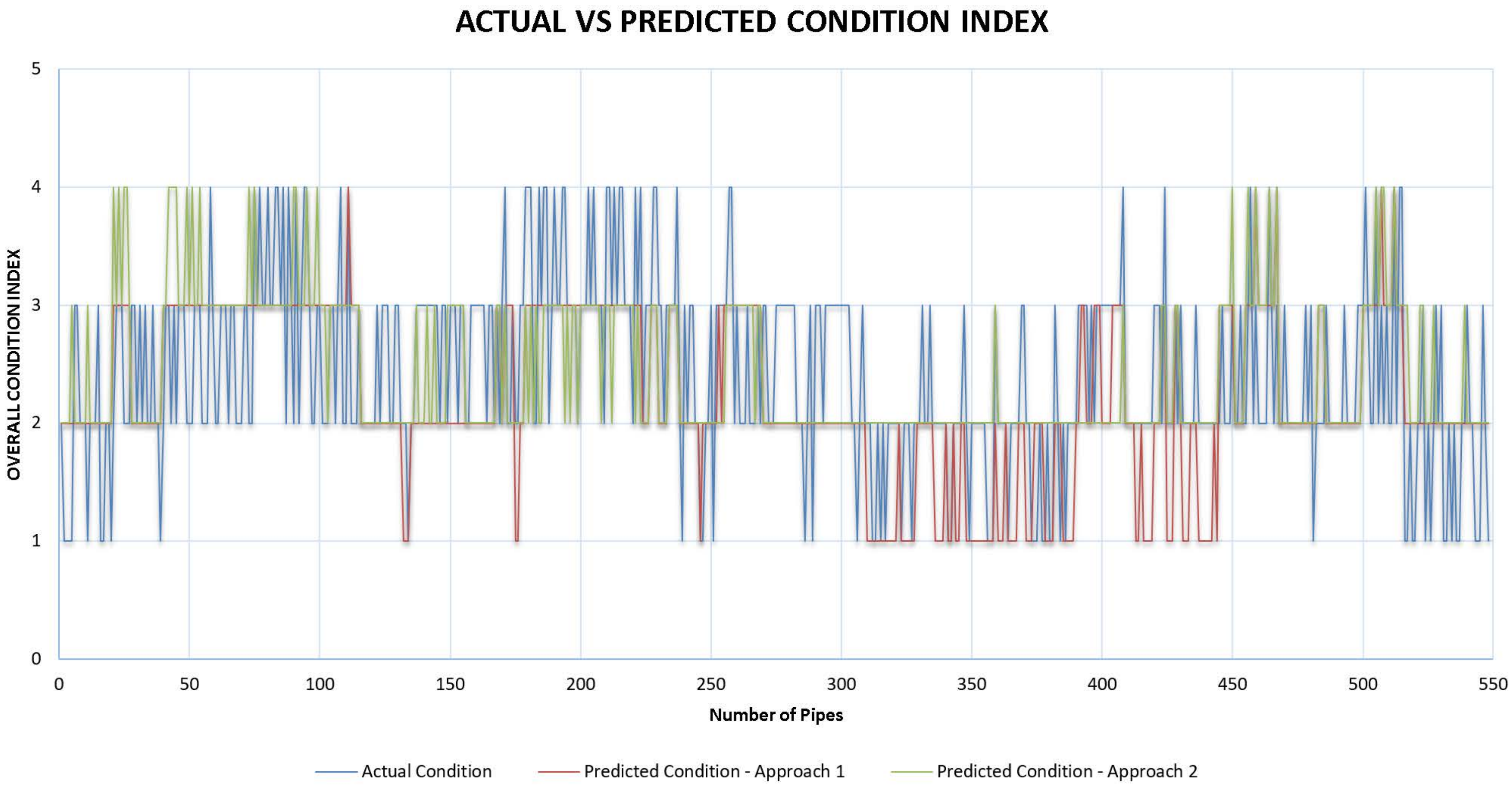


Figure 5-10: Actual versus Predicted Overall Condition Index (2)

CHAPTER 6: CONCLUSION

New condition assessment models for sewer networks developed by integrating FANP and Monte-Carlo simulation as one approach and FANP combined with Monte-Carlo simulation, FST and ER as another approach were presented in this research. Seventeen factors grouped under physical, environmental and operational categories for gravity pipelines in addition to the operating pressure for pressurized pipelines were considered in the model. The developed models use a weighted scoring system to determine a numerical value indicating the condition of pipelines based on the effecting factors' relative weights and effect values. The relative weights and degree of influence of the different factors were elicited from a questionnaire that was distributed to experts working in the field of infrastructures and sewage networks.

The considered factors were grouped under physical, environmental and operational categories. The relative weight for each factor and category was determined by the FANP and Monte-Carlo Simulation module that considered the uncertainties and fuzziness associated with transforming the experts' judgments into numerical values. The sub-factors for the physical, environmental and operational categories recorded importance weights varying within the range of 8%. The "Ground Disturbance" factor was found to be the most influential factor followed by the "Location" with a weight of 10.6% and 9.3% for pipelines under gravity and 8.8% and 8.6% for pipelines under pressure, respectively. On the other hand, the least affecting factor was the "Length" followed by "Diameter" with a weight of 2.2% and 2.5% for pipelines under gravity and 2.5% and 2.6% for pipelines under pressure.

For the first approach, Monte-Carlo simulation is used to determine the final scores for the weights by probability distribution fitting, which helped in eliminating the uncertainties accompanying the model's outputs due to different weights.

For the second approach, FST module was used to create membership functions and thresholds for the effect values of the different effecting factors in the form of triangular and trapezoidal functions. The overall condition index was determined by using the ER module with the aid of FST in which degrees of belief were set and combined with different relative weights of the different factors. Fuzzy membership functions' were defuzzified by utilizing the FST to convert the fuzzy overall condition into a crisp value.

The developed models were validated using actual inspection data for 549 existing sewer gravity pipelines in Qatar. Results obtained by the first approach were 15%, 85%, 0.12, 0.15, and 893 and by the second approach were 14%, 86%, 0.16, 0.11, and 898 for AIP, AVP, MAE, RMSE and f_i, respectively, which indicates that the developed model would yield in sound and reliable results .

The proposed condition assessment model can provide key personal and decision makers with a proper tool to plan their inspections instead of using conventional inspection and assessment methods that are time consuming and costly, collect only necessary data and provide cost effective rehabilitation and maintenance action.

The model presented in this paper can be improved by adding and considering additional factors other than those mentioned and more case studies can be used to expand data sets to validate and calibrate the model. In addition, increasing number of questionnaires' participants or using other techniques to determine relative weights of contributing factors is recommended for future work.

Recommendations for future research:

1. Standardization of data acquisition tool for municipalities which should cover all relevant physical, operational and environmental factors.
2. Extension of the sewer pipeline condition prediction methodology to other sewer network structures such as manholes, pumping stations, etc.
3. Application of sewer condition prediction to other infrastructure networks.
4. Develop a tool integrated with GIS.
5. Develop a flexible tool that allows users to add or remove affecting factors or adjust the factor's weights.

REFERENCES

Achim, D., Ghotb, F., and McManus, K. J., (2007), “Prediction of water pipe asset life using neural networks”, J. of Infra. Syst, 13(1), 26-30.

Agresti, A., (2002), “Categorical data analysis”, 2nd Ed., Wiley, Hoboken, New Jersey.

Al-Barqawi, H., and Zayed, T., (2008), “Infrastructure Management: Integrated AHP/ANN Model to Evaluate Municipal Water Mains’ Performance”, ASCE, Journal of Infrastructure Systems, 10.1061/ (ASCE) 1076-0342.

Al-Barqawi, H., and Zayed, T., (2006), “Assessment Model of Water Main Conditions”, Proc., Pipeline Division Specialty Conference, ASCE, Chicago, Illinois, USA.

Allison, P., (1999), “Multiple regression: a primer”, Pine Forge Press, Thousand Oaks, CA.

Ana E V, Bauwens W, (2010), "Modeling the structural deterioration of urban drainage pipes: The state-of-the-art in statistical methods", Urban Water Journal, 7, 47-59.

Ana E V, (2009), "Sewer asset management - sewer structural deterioration modeling and multi-criteria decision making in sewer rehabilitation projects prioritization", PhD thesis, Department of Hydrology and Hydraulic Engineering, Vrije Universiteit Brussel, Brussel.

Ana, E., Bauwens, W., Pessemier, M., Thoeye, C., Smolders, S., Boonen, I. and De Gueldre, G., (2009), “An investigation of the factors influencing sewer structural deterioration”, Urban Water Journal, 6(4), 303-312.

Ariaratnam S T, El-Assaly A, Yang Y, (2001), "Assessment of infrastructure inspection needs using logistic models", Journal of Infrastructure Systems ,7 ,160-165.

Bai, H., Sadiq, R., Najjaran,H., Rajani, B., (2008), ”Condition assessment of buried pipes using hierarchical evidential reasoning model”, Journal of Computing in Civil Engineering, 22(2), 114-122.

Baik H S, Jeong H S, Abraham D M, (2006), "Estimating transition probabilities in Markov chain-based deterioration models for management of wastewater systems", Journal of Water Resources Planning and Management, 132 15-24.

Baur R, Herz R, (2002), "Selective inspection planning with ageing forecast for sewer types”, Water Science and Technology 46 (6-7) 389-396.

Baur R, Zielichowski-Haber W, Kropp I, (2004), "Statistical analysis of inspection data for the asset management of sewer networks", Proceedings 19th EJSW on Process Data and Integrated Urban Water Modeling, Lyon, France.

Bayer, C., Hoel, H., Von Schwerin, E., Tempone, R., (2014), “On non-asymptotic optimal stopping criteria in Monte Carlo simulations”, SIAM J. Sci. Comput. , 36(2), A869–A885.

British Standards Institution (BSI), (2012)."Investigation and assessment of drain and sewer systems outside buildings-General Requirements". BSI, London. ISBN: 978-0-580-70190-0.

Butler, D & Davis, J, (2000), “Urban Drainage”, Taylor and Francis Group, New York, USA

Chae, M.J., Iseley, T., and Abraham, D.M., (2003), “Computerized sewer pipe condition assessment”, In: Proceedings International Conference on Pipeline Engineering and Construction, Baltimore, MD.

Chughtai, F., and Zayed, T., (2007a), “Sewer pipeline operational condition prediction using multiple regression”, Proc., Pipelines 2007: Advances and Experiences with Trenchless Pipeline Projects., ASCE, Reston, VA.

Chughtai, F., and Zayed, T., (2007b), “Structural condition models for sewer pipeline”, Proc., Pipelines 2007: Advances and Experiences with Trenchless Pipeline Projects., ASCE, Reston, VA.

Chughtai F, Zayed T., (2008), "Infrastructure condition prediction models for sustainable sewer pipelines", Journal of Performance of Constructed Facilities ,22, 333-341.

Daher,S., (2015), “Defect-based Condition Assessment Model and Protocol of Sewer Pipelines”, Msc., Concordia University, Montreal, Canada.

Davies J P, Clarke B A, Whiter J T, Cunningham R J, (2001), "Factors influencing the structural deterioration and collapse of rigid sewer pipes", Urban Water ,3, 73-89.

Davies, J., P., (2001), “Application of interaction matrices to the problem of sewer collapse”, Proceedings of the 11th European sewage and refuse symposium, liquid waste section., Munich, Germany.

Davies, J., P., Clarke, B., A., Whiter, J., T., Cunningham, R.J., and Leidi, A., (2001), “The structural condition of rigid sewer pipes: a statistical investigation”, Urban Water Journal, 3, 277-286.

Dikmen, I., Birgonul, M., and Kiziltas, S., (2005), “Prediction of Organizational Effectiveness in Construction Companies”, Journal of Construction Engineering and Management, 131(2), 252–261.

Dirksen J, Clemens F H L R, (2008), "Probabilistic modeling of sewer deterioration using inspection data", Water Science and Technology, 57 (10), 1635-41.

Durkin, J., (1994), “Expert systems: design and development”, Prentice Hall PTR.

Elmasry, M., Zayed, T., and Hawari, A., (2016), “Sewer Inspection Prioritization Using a Defect-Based Bayesian Belief Network Model”, ASCE Pipelines 2016, VA, 613-625.

El-Assaly, A., Ariaratnam, S.T., Ruwanpura, J., and Ng, H., (2006), “Cost forecast model for sewer infrastructure”, Municipal Engineer, 159 (3), 155–160.

Fausset, L., (1994), “What is a Neural Net?”, Fundamentals of neural networks: architectures, algorithms, and applications D. Fowley, B. Baker, and A. Dworkin, eds., Prentice Hall, Englewood Cliffs, NJ., 3 - 4.

Fenner, R.A., (2000). “Approaches to sewer maintenance: a review”, Urban Water, 2, 343-356.

Fenner, R. A., Sweeting, L., and Marriott, M., (2000), “A new approach for directing pro-active sewer maintenance”, Proceedings of the institution of civil engineers, water and maritime Engineering Journal, 142(2), 67 – 78.

German Association for Water, Wastewater and Waste (DWA), (2015), "State detection and assessment of drain and sewer systems outside buildings-Part 3: Assessment by optical inspection", DWA, Germany. ISBN: 978-3-88721-224-7.

Hahn, M. A., Palmer, R. N., Merrill, M. S., and Lukas, A. B., (2002), “Expert System for Prioritizing the Inspection of Sewers: Knowledge Base Formulation and Evaluation”, J. Water Resources Planning and Mngt., 128(2), 121 – 129.

Hajmeer, M., & Basheer, I., (2002), “A probabilistic neural network approach for modeling and classification of bacterial growth/no-growth data”, Journal of microbiological methods, 51(2), 217-226.

Hawari, A., Alkadour, F., Elmasry, M. and Zayed, T., (2016), “Simulation-Based Condition Assessment Model for Sewer Pipelines”, Journal of Performance of Constructed Facilities, 04016066.

Herz R., (1996), "Aging Processes and Rehabilitation needs of Drinking Water distribution networks", Journal of Water Resources Planning and Management, 45, 221-231.

Herz R., (1995), "Alterung und Erneuerung von Infrastruturbeständen - ein Kohoertenüberlebensmodell", Jahrbuch für Regionalwissenschaft Jg., 14/15, 5-29.

Horold, S. and Baur, R., (1999), "Modeling sewer deterioration for selective inspection planning – case study Dresden", Proceedings 13th EJSW on Service Life Management Strategies of Water Mains and Sewers, 8–12 September, Switzerland.

Horold, S., (1998), "Forecasting rehabilitation needs: Evaluation of the AQUA WertMin software for service life and total cost estimation", SINTEF Report, Trondheim, Norway.

Inomata, T., Onogi, K., Nakata, Y., & Nishimura, Y, (1988), "A rule-based simulation system for discrete event systems", Journal of chemical engineering of Japan, 21(5), 482-489.

Jansen, K., (2007), "AQUA-WertMin program manual", Klienbittersdorf, Germany: Expert Office for Sewer Rehabilitation.

Khan Z, Zayed T, Moselhi O, (2010), "Structural condition assessment of sewer pipelines", Journal of Performance of Constructed Facilities, 24, 170-179.

Kleiner Y, Rajani B, and Wang S, (2007), "Consideration of static and dynamic effects to plan water main renewal", Proceedings Middle East Water 2007, 4th International Exhibition and Conference for Water Technology, Manama, Bahrain.

Kleiner, Y., Sadiq, R., and Rajani, B., (2004), “Modeling failure risk in buried pipes using fuzzy markov deterioration process”, Proc., Pipeline Engineering and Construction: What’s on the Horizon?, ASCE, Reston,VA., 1-12.

Kleiner. Y., (2001), “Scheduling inspection and renewal of large infrastructure assets”, J. Infrastruc. Syst., 7(4), 136 – 143.

König A, (2005), "WP2 External Corrosion Model Description", Computer Aided REhabilitation of Sewer networks (Care-S), SINTEF Technology and Society, Trondheim, Norway.

Lawless, J.F., (1982), "Statistical models and methods for lifetime data", New York: John Wiley and Sons.

Le Gat Y, (2008), "Modeling the deterioration process of drainage pipelines", Urban Water Journal, 5, 97-106.

Lee, H., (1996), “Applying fuzzy set theory to evaluate the rate of aggregative risk in software development, Fuzzy Sets and Systems”, 79, 323-336.

Mamdani, E. H., and Assilian, S., (1975), “An experiment in linguistic synthesis with a fuzzy logic controller”, International Journal of Man-Machine Studies, 7, 1 – 13.

Marlow D, Davis P, Trans D, Beale D, Burn S, (2009), "Remaining Asset Life: A State of the Art Review", Final Report, Water Environment Research Fundation (WERF), Alexandria, VA, US

MATLAB and Statistics Toolbox Release 2012b, The MathWorks, Inc., Natick, Massachusetts, United States.

Mehle J, O´Keefe, Wrase P, (2001), "An Examination of Methods for Condition Rating of Sewer Pipelines", Center for development of technical leadership, University of Minnesota.

Micevski T, Kuszera G, Coombes P, (2002), "Markov model for storm water pipe deterioration", Journal of Infrastructure Systems, 8(2) , 49-56.

Mikhailov, L., (2004), “A fuzzy approach to deriving priorities from interval pairwise comparison judgments”, European Journal of Operational Research, 159, 687-704.

Müller K, Dohmann M, (2002), “Entwicklung eines allgemein anwendbaren Verfahrens zur selektiven Erstinspektion von Abwasserkanälen und Anschlussleitungen”, Bundesministerium für Bildung und Forschung (bmb+f), Aachen, Germany.

Müller, K., (2002), “Development of a generally applicable methodology for selective inspection of sewer networks”, Part A: scientific studies. Final report of the Institute of Urban Water Management ISA, RWTH Aachen University, Aachen, Germany.

Muller, K. and Fischer, B., (2007), “Objective condition assessment of sewer systems”, In: Proceedings IWA 2nd Leading-Edge Conference in Asset Management, Lisbon, Portugal.

NRC., (2003), “Infiltration/Inflow Control/Reduction for Wastewater Collection Systems: A Best practice”, National Guide to Sustainable Municipal Infrastructure, Issue No. 1.0, Federation of Canadian Municipalities, National Research Council of Canada, Canada.

Najafi, M., and Kulandaivel, G., (2005), “Pipeline condition prediction using neural network models”, Proc., Pipeline 2005: Optimizing Pipeline Design, Operations and Maintenance in Today’s Economy, ASCE, Reston, VA., 767 – 781.

Piantanakulchai, M., (2005), “Analytic network process model for highway corridor planning”, Proceedings of ISAHP 2005.

Pohar, M., Blas, M., & Turk, S., (2004), “Comparison of logistic regression and linear discriminant analysis: a simulation study”, Metodoloski zvezki, 1(1), 143.

Rajani, B., and Kleiner, Y., (2001). “Comprehensive review of structural deterioration of water mains: statistical models”, Urban water, 3(3), 131-150.

Rajani B, Kleiner Y, and Sadiq R, (2006), “Translation of Pipe Inspection Results Into Condition Ratings Using The Fuzzy Synthetic Evaluation Technique”, Journal of Water Supply Research and Technology-Aqua, 55, 11-24.

Ross, S. M., (2000), “Introduction to probability methods”, 7th Edition, Academic Press, San Diego, California.

Raychaudhuri, S., (2008), “Introduction to Monte Carlo Simulation”, Proc, Simulation Conference, IEEE, Austin, Texas, USA.

Ruwanpura, J., Ariaratnam, S., and El-Assaly, A., (2004), “Prediction models for sewer infrastructure utilizing rule-based simulation”, Civ. Eng. Environ. Syst., 21(3), 169 – 185.

Ruwanpura, J., Ariaratnam, S.T., and El-Assaly,A., (2004), “A Rule-based simulation models for sewer infrastructure”, Proceedings of the Construction Research Congress,ASCE, Honolulu, Hawaii, USA.

Saaty, T. J, (1996), “Decision making in Complex Environments”, The Analytical Hierarchy Process for decision Making with Dependence and Feedback. USA: RWS Publications.

Sadiq, R., Kleiner, Y., and Rajani, B. B., (2004), “Fuzzy cognitive maps for decision support to maintain water quality in aging water mains”, NRCC-47305, 4th Int. Conf. on Decision-Making in Urban and Civil Engineering (DMUCE 4), Porto, Portugal, 1-10.

Sage, G. H., (1990), “Power and ideology in American sport: A critical perspective”, Human Kinetics Publishers.

Salem, O., AbouRizk, S., and Ariaratnam, S., (2003), “Risk-based life-cycle costing of infrastructure rehabilitation and construction alternatives”, J. Infrastruct. Syst., 9(1), 6-15.

Salman B, (2010), "Infrastructure Management and Deterioration Risk Assessment of Wastewater Collection Systems", PhD thesis, University of Cincinnati.

Scheidegger A, Hug T, Rieckermann J, Maurer M, (2011), "Network condition simulator for benchmarking sewer deterioration models", Water Research, 45 ,4983-4994.

Schmidt T, (2009), “Modellierung von Kanalalterungsprozessen auf der Basis von Zustandsdaten”, PhD thesis, Institut für Stadtbauwesen und Straßenbau, Technical University Dresden, Dresden, Germany.

Sinha, S., and McKim, R. A., (2007), “Probabilistic based integrated pipeline management system”, Tunneling and Underground Space Tech., 22(5-6), 543 – 552.

Specht, D. F., (1990), “Probabilistic neural networks”, Neural networks, 3(1), 109-118.

Tran D H, Perera B J C, Ng A W M, (2007), "Neural network based prediction models for structural deterioration of urban drainage pipes, Land, Water and Environmental Management: Integrated Systems for Sustainability", Proceedings, Christchurch pp 2264-2270.

Tran D, (2007), “Investigation of deterioration models for stormwater pipe systems”, PhD thesis, School of Architectural, Civil and Mechanical Engineering, Victoria University.

Vanier, D.J., (2001), “Why industry needs asset management tools”, Journal of Computing in Civil Engineering, 15 (1), 35–43.

Vollersten J, König A, (2005), "WP2 Report D6: Model testing and evaluation, Computer Aided REhabilitation of Sewer networks (Care-S)", SINTEF Technology and Society, Trondheim, Norway.

Wirahadikusumah, R., Abraham, D.M., Iseley, T. and Prasanth, R.K., (1998), “Assessment technologies for sewer system rehabilitation”, Automation in Construction, 7, 259-270.

Wirahadikusumah R, Abraham D, Iseley T, (2001), "Challenging issues in modeling deterioration of combined sewers", Journal of Infrastructure Systems, 7, 77-84.

WRc, (2001), Manual of Sewer Condition Classification - 4th Edition, Water Research Centre, UK.

Yang, J., (2004), “Road crack condition performance modelling using recurrent Markov chains and artificial neural networks”, Doctoral Dissertation, Department of Civil and Environmental Engineering, College of Engineering, University of South Florida.

Yang, J.B., (2001), “Rule and utility based evidential reasoning approach for multi-attribute decision analysis under uncertainties”, European Journal of Operational Research, 131, 31–61.

Yang, J.B., Sen, P., (1994), “A general multi-level evaluation process for hybrid MADM with uncertainty”, IEEE Transactions on Systems, Man, and Cybernetics, 24 (10), 1458–1473.

Yang, J.B., Singh, M.G., (1994), “An evidential reasoning approach for multiple attribute decision making with uncertainty”, IEEE Transactions on Systems, Man, and Cybernetics, 24 (1), 1–18.

Yang, J.B., and Xu, D.L., (2002), “On the Evidential Reasoning Algorithm for Multiple Attribute Decision Analysis under Uncertainty”, IEEE Transaction on Systems, Man, and Cybernetics, Part A: Systems and Humans, Vol. 32, No. 3, pp. 289-304.

Yan, J. M., & Vairavamoorthy, K., (2003), “Prioritizing water mains rehabilitation under uncertainty”, Advances in water supply management, 237-246.

Younis, R., and Knight, M.A., (2010), “Continuation ratio model for the performance behavior of wastewater collection networks”, Tunneling and Underground Space Technology, 25, 660-669.

Zadeh, L. A., (1965), “Fuzzy sets”. Information and Control”, 8, 338–353.

Zayed, T., and Halpin, D, (2005), “Deterministic Models for Assessing Prod. And Cost Of Bored Piles”, Journal of Construction Management and Economics, 23(5), 531-543.

Zhou, Xiaoguang, (2012), “Fuzzy Analytical Network Process Implementation with Matlab”, MATLAB - A Fundamental Tool for Scientific Computing and Engineering Applications Volume 3, Prof. VasiliosKatsikis (Ed.), ISBN: 978-953-51-0752-1.

Zou, J. Han, Y, and So, S-S., (2008), “Overview of Artificial Neural Networks”, Artificial Neural Networks: Methods and Applications, D. J. Livingstone, ed., Humana Press, Totowa, New Jersey.

APPENDIX: QUESTIONNAIRE

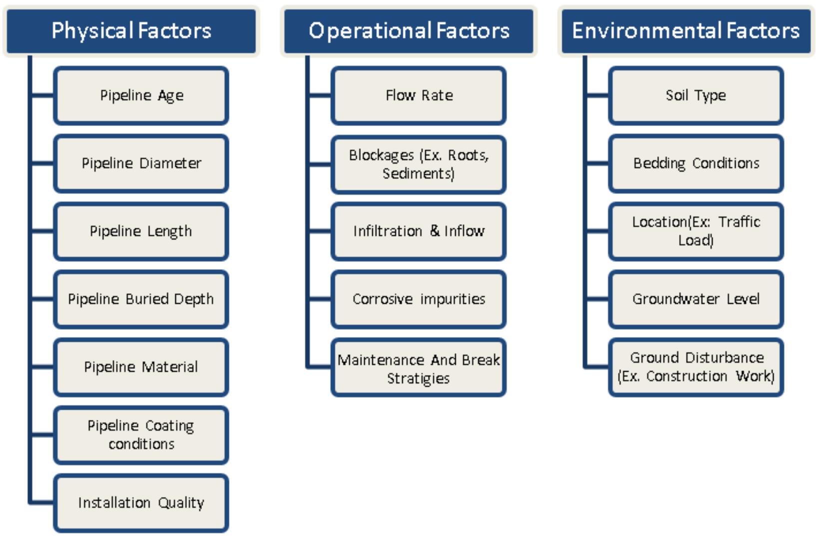
Department of Civil & Architectural Engineering

CONDITION ASSESSMENT OF SEWER PIPELINES

(FLOW UNDER GRAVITY & PRESSURE (RAISING MAINS))

Dear Sir/Madam

We would like to present our appreciation and thanks to you for taking part of your time to complete this questionnaire. This questionnaire aims to identify the degree of importance of the factors affecting the assessment of sewer pipelines' condition. This questionnaire is a part of the requirements for an academic research which is done under the supervision of Qatar and Concordia Universities funded by Qatar National Research Fund (QNRF) to build a condition assessment model for sewer pipelines. The information in the questionnaire will be used for academic research with complete commitment for absolute confidential to your information. Based on literature review and interviews with experts, the main factors that were found to have an effect on the sewer pipelines' condition can be summarized as shown in Figure 1 below:



After reviewing the main factors listed; please kindly fill in parts (1) to (3) of this questionnaire.

PART (1) : GENERAL INFORMATION

1) **How do you describe your occupation?** ---

2) **How long is your working experience?** --

PART (2): PAIRWISE COMPARISON BETWEEN FACTORS

In an attempt to determine the degree of importance of factors affecting the condition of Sewer Pipelines, kindly fill the tables in the next pages by ticking (✓) in the appropriate box based on your point of view:

Example:

*In the table below, consider comparing **"Pipeline Age"** (Criterion X) with **"Pipeline Diameter"** (Criterion Y) with respect to **"Physical Factors"**.*

PHYSICAL FACTORS										
	← Degree of Importance →									
Criterion (X)	**(9)** Absolute	**(7)** Very Strong	**(5)** Strong	**(3)** Moderate	**(1)** Equal	**(3)** Moderate	**(5)** Strong	**(7)** Very Strong	**(9)** Absolute	**Criterion (Y)**
Pipeline Age			✓							Pipeline Diameter
					✓					Pipeline Length
									✓	Pipeline Buried Depth
										Pipeline Material
										Pipeline Coating conditions
										installation Quality

*If you consider that Pipeline Age" is more important than Pipeline Diameter" and the degree of this importance is **"Strong"** then tick (✓) here*

*If you consider both "Pipeline Age" and "Pipeline Length" have **"Equal"** importance; then tick (✓) here.*

*If you consider the "Pipeline Buried Depth" is more important than "Pipeline Age" and the degree of importance is **"Absolute"** then tick (✓) here*

*The same procedure is then followed when comparing **"Pipeline Age"** with **the other factors**.*

1) <u>**Pair wise Comparison (Sewer Pipelines Under Gravity):**</u>

Criterion (X)	← **Degree of Importance** →									**Criterion (Y)**
	(9) Absolute	**(7) Very Strong**	**(5) Strong**	**(3) Moderate**	**(1) Equal**	**(3) Moderate**	**(5) Strong**	**(7) Very Strong**	**(9) Absolute**	
SEWER PIPELINES CONDITION										
Physical Factors										Environmental Factors
										Operational Factors
PHYSICAL FACTORS										
Pipeline Age										Pipeline Diameter
										Pipeline Length
										Pipeline Buried Depth
										Pipeline Material
										Pipeline Coating conditions
										installation Quality
OPERATIONAL FACTORS										
Corrosive Impurities										Blockages (Ex. Roots, Sediments)
										Infiltration & Inflow
										Flow Rate
										Maintenance And Break Record
ENVIRONMENTAL FACTORS										
Groundwater Level										Soil Type
										Bedding Conditions
										Location (Ex. Traffic Load)
										Ground Disturbance (Ex. Construction Work)
PHYSICAL FACTORS										
Environmental Factors										Operational Factors
ENVIRONMENTAL FACTORS										
Physical Factors										Operational Factors
OPERATIONAL FACTORS										
Physical Factors										Environmental Factors

2) <u>Pair wise Comparison (Sewer Pipelines Under Pressure):</u>

Criterion (X)	Degree of Importance									Criterion (Y)
	(9) Absolute	(7) Very Strong	(5) Strong	(3) Moderate	(1) Equal	(3) Moderate	(5) Strong	(7) Very Strong	(9) Absolute	
SEWER PIPELINES CONDITION										
Physical Factors										Environmental Factors
										Operational Factors
PHYSICAL FACTORS										
Pipeline Age										Pipeline Diameter
										Pipeline Length
										Pipeline Buried Depth
										Pipeline Material
										Pipeline Coating conditions
										installation Quality
OPERATIONAL FACTORS										
Corrosive Impurities										Blockages (Ex. Roots, Sediments)
										Infiltration & Inflow
										Flow Rate
										Maintenance And Break Record
										Operating Pressure
ENVIRONMENTAL FACTORS										
Groundwater Level										Soil Type
										Bedding Conditions
										Location (Ex. Traffic Load)
										Ground Disturbance (Ex. Construction Work)
PHYSICAL FACTORS										
Environmental Factors										Operational Factors
ENVIRONMENTAL FACTORS										
Physical Factors										Operational Factors
OPERATIONAL FACTORS										
Physical Factors										Environmental Factors

PART (3): DETERMINING THE SCORE OF FACTORS

In order to determine the condition index; it is required to determine the score of factors. Based on your experience, please fill and/or add your modifications to the table according to the following:

- An **effect value range on accessories condition** from 0 to 10, where **"0"** represents the **worst effect** and **"10"** represents the **best effect** on accessories condition.

Example:

*In the table below, consider evaluating the **"Pipeline Age"** factor.*

Main Factor	Sub-factors	Unit Of Measure	Qualitative Description (Parameters)	Effect Value Range On Pipeline Condition (0 – 10)
PHYS ICAL	Pipeline Age	(Years)	Old	*0 to 3*
			Medium	*4 to 7*
			New	*8 to 10*

*The "Effect Value Range" can be "**0 to 3**", "**4 to 7**", and "**8 to 10** " for the "old", "Medium", and "New" parameters respectively.*

Main Factor (A)	Sub-factors (B)	Unit Of Measure (C)	Qualitative Description (Parameters) (D)	Effect Value On Sewer Gravity Pipelines (0 – 10) (E)	Effect Value On Sewer Pressurized Pipelines (0 – 10) (F)
PHYSICAL	Pipeline Age	(Years)	Old >30		
			Medium (15-30)		
			New <15		
	Pipeline Diameter	(m)	Small <300		
			Medium (300-600)		
			Large >600		
	Pipeline Length	(m)	Short <500		
			Medium (500-2000)		
			Long >2000		
	Pipeline Buried Depth	(m)	Shallow <4		
			Moderate (4-6)		
			Deep >6		

Main Factor (A)	Sub-factors (B)	Unit Of Measure (C)	Qualitative Description (Parameters) (D)	Effect Value On Sewer Gravity Pipelines (0 – 10) (E)	Effect Value On Sewer Pressurized Pipelines (0 – 10) (F)
	Pipeline Material	(%)	Poor		
			Fair		
			Good		
	Pipeline Coating Conditions	(%)	Poor		
			Fair		
			Good		
	Installation Quality	(%)	Poor		
			Fair		
			Good		
OPERATIONAL	Flow Rate	(m^3/d)	Low		
			Medium		
			High		
	Blockages (Ex. Roots, Sediments)	(%)	Low		
			Medium		
			High		
	Infiltration & Inflow	($m^3/d/m$)	Low		
			Medium		
			High		
	Corrosive Impurities	(%)	Non-aggressive		
			Moderate		
			Aggressive		
	Maintenance And Break Strategies	(%)	Poor		
			Fair		
			Good		
ENVIRONMENTAL	Soil	Type	Rock		
			Sand		
	Bedding Conditions	(%)	Poor		
			Fair		
			Good		
	Location	Surface Type	Asphalt		
			Seal		
			Foot Path		
			Unpaved		
	Groundwater Level	Pipe position	Above Groundwater		
			Below Groundwater		
	Ground Disturbance	(%)	Low		
			Moderate		
			High		