Asset Management Tools for Sustainable Water Distribution Networks

Zahra Zangenehmadar

A Thesis

In the Department of

Building, Civil and Environmental Engineering

Presented in Partial Fulfillment of the Requirements

For the Degree of

Doctor of Philosophy (Civil and Environmental Engineering) at

Concordia University

Montreal, Quebec, Canada

August 2016

© Zahra Zangenehmadar, 2016

Concordia University

SCHOOL OF GRADUATE STUDIES

This is to certify that the thesis prepared

By: Zahra Zangenehmadar

Entitled: Asset Management Tools for Sustainable Water Distribution Networks

and submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY (Civil Engineering)

complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final examining committee:

Dr. N. Bhuiyan	Chair
Dr. Ahmed Bouferguene	External Examiner
Dr. G. Gopakumar	External to Program
Dr. Z. Zhu	Examiner
Dr. T. Zayed	Examiner
Dr. O. Moselhi	Thesis Supervisor

Approved by: ____

ABSTRACT

Water Distribution Network (WDN) is the most important element in water supply systems. According to the Canadian Water and Wastewater Association (CWWA), there are more than 112,000 kilometers of water mains in Canada and their replacement cost is estimated to be $34 billion. Since majority of pipelines are frequently above 100 years old, they are prone to failure and outbreaks of disease derivable to drinking water are inevitable. Breakage in water infrastructure can result in disruptions and damage to other surrounding infrastructure such as road networks or structures. Moreover, unscheduled emergency rehabilitation works can cause interruption to traffic, households and businesses. Therefore, it is important to assess the unknown condition of WDNs to find their respective rate of deterioration in order to prevent disastrous failures or sudden shutdowns.

Determining pipe condition through cost-effective assessments will grant very poor condition pipes to be considered first in order to avoid related risk and devastating failures. The problem here is that in most cases, there are limited data about condition of water mains due to the underground location of the pipelines and their restricted access. Several pipes were installed 100 years ago and they have not been examined until a problem occurred. An extensive literature review shows the absence of comprehensive and generalized maintenance model for scheduling the rehabilitation and replacement of individual pipelines in the whole network based on their remaining useful life. Previous research efforts concentrated mostly on developing models, which utilize long-term data and consider solely the pipe segments not the whole network. Since pipe segments are connected together, the performance of one pipe affect the performance of other pipes in the neighborhood. This is the reason that pipes should be considered as a network rather than individual pipeline. This shows the need for a model which could forecast the behavior of each pipeline and the whole network based on available data simultaneously.

This study aims to develop a model that can predict remaining useful life to optimize the needed intervention plans based on the available budget. For this purpose, a statistical condition model is developed which utilizes characteristics of a pipeline to predict its condition. In this model, Delphi study identifies the most important factors affecting deterioration of water pipelines at first, through three rounds of questionnaires sent to selected experts. The findings show that important factors are mainly physical factors such as pipe age, pipe material, etc. After that, Fuzzy Analytical Hierarchy Process (FAHP) and Entropy Shannon are employed to prioritize the selected factors in previous step and calculate their weights based on their relative importance. Results reveal that pipe installation, age and material are the most effective parameters in deterioration. These weights are used to find the condition index of the pipeline from pipe characteristics, soil and water properties. Upon determining the condition index, the remaining useful life is estimated using the developed artificial neural network (ANN). Ultimately, the budget is allocated efficiently and different repair and replacement strategies are scheduled based on the remaining useful life and breakage rate of the pipelines utilizing the developed near optimum Genetic Algorithm (GA)-based model. Data of the water distribution network of the city of Montréal is used to develop, train and validate the developed models. Results indicate that 30.7 km of the pipelines of Montreal should be replaced in the next 20 years and 2610 km are in need of both major and minor rehabilitations. This research proposes a framework for optimized replacement and maintenance plans based on the remaining

useful life and condition of the pipelines which will help operators for efficient budget allocation and better management of needed intervention plans.

ACKNOWLEDGEMENTS

My deepest acknowledgement is to God. I would like to express my sincere gratitude to my supervisor Professor Osama Moselhi for the continuous and invaluable support of my Ph.D study and related researches, for his patience, motivation, and immense knowledge. His guidance helped me in all the time of research and writing of this thesis. I believe without his gaudiness and directness; this research would have been more challenging.

Besides my supervisor, I would like to thank Prof. Tarek Zayed, Dr. Zhenhua Zhu and Dr. Govind Gopakumar for their not only insightful comments and constrictive feedback, but for the hard question, which incented me to widen my research from various perspectives.

My sincere thanks also goes to my fellow lab mates, Dr. Laya Parvizsedghy, Mr. Sasan Golnaraghi, Mr. Farzad Karimian, Dr. Mona Abouhamed, Mrs. Thikra Dawood and all my friends who provided me with their helpful comments and stimulating discussions as my colleagues at the Construction Automation Lab. I had the opportunity to work in a proficient and welcoming atmosphere that was ethnically and intellectually diverse.

I owe my deepest gratitude to my closest friend and roommate in Montreal Fahime Soleymani for her affectionate help and endless support throughout my work.

Many thanks also go to my friends Azadeh Dastmalchi, Leila Jamaat, Alireza Zandi Karimi and Dr. Roshanak Vesali for their support and encouragements.

Sincere appreciation goes to my parents (Dr. Batoul Khosravi and Mr. Khalil Zangeneh madar) and my siblings (Maryam and Mohammad Ebrahim) for their infinite love and care throughout writing this thesis and my life in general.

Last but not the least, I would like to thank the person who has always stood by my side, the one who has provided me with his continuous love and understanding, to the love of my life, my wonderful husband Nima Razagh Pour.

To my Beloved Mother and Dear Father

And

My Husband Nima

Table of Contents

List of Figures

List of Tables

CHAPTER 1: INTRODUCTION

1.1. Problem statement and research motivation

Water Distribution Network (WDN) is reported to be the most expensive part of water supply systems (Giustolisi et al. 2006) since it is largely spread underneath the ground surface. WDN is also the significant element in providing the healthy drinking water. According to the 2013 ASCE's report card for America's infrastructure, 21st century is specified as the end of useful life for most of the water distribution networks in the US. It is predicted that 240,000 breaks will happen per year and the cost of replacement estimated to be $1 trillion assuming every pipe needs to be replaced. Moreover, the recent 2016 Canadian Infrastructure report card for drinking water stipulates that 29% of the drinking water systems all over Canada is rated fair to very poor and the replacement value of these assets is estimated to be $24.5 billion.

Therefore, it is important to monitor and assess the condition of these networks throughout the time since knowing the long-term condition of pipeline helps in finding the rate at which it depreciates. Identifying the deterioration rates and the remaining useful life will help in performing more economical and cost-efficient replacement and maintenance measures such as preventing from premature renewal of excellent condition pipes to save money and time. In a number of cases, data needed for generating and estimating condition and subsequently remaining useful life may be insufficient. It could be of the reason that pipelines are located underground and access to them is restricted. Subsequently, prediction models should be employed to forecast the behavior of the pipelines based on the available data such as pipe design. Consequently, it is supposed to be a high demand for these assessment models over the next two decades.

Although this subject has been studied extensively in the literature, however the existing studies have undergone several limitations. As a way of illustration, only a few of the reported studies focused on the whole network instead of individual pipe segments for developing a maintenance and replacement program. Moreover, they rarely entailed application of both remaining useful life and breakage rate to identify and determine the segments of pipeline that need to undergo a measure. This study aims to develop a budget allocation and residual life prediction models for water distribution network based on the condition and breakage rate of pipe segments. The models will be utilized in developing a comprehensive value-driven optimized intervention plans and ease selecting the rehabilitation and replacement strategies efficiently.

1.2. Objectives

The main objective of this research is to study current practices, optimization tools and techniques used in prediction of leakage in water distribution networks and ultimately develop an integrated optimization model for value-driven budget allocation at network level to achieve the following sub-objectives:

- Develop a multi-attributed condition index
- Predict the remaining useful life of pipe segments
- Establish rehabilitation and replacement planning model

1.3. Research methodology

The methodology of this research is broadly described in Chapter 3. It consists of the following main steps which are summarized below:

1. **Literature Review**

   The existing researches are reviewed to find those works that are similar to performance prediction models in water distribution network such as condition rating, deterioration and life prediction of pipe segments. It also covers the different techniques that have been used in model development of this research.

2. **Delphi Survey**

   Delphi survey is performed to find the most important factors affecting the deterioration of water pipeline based on different perspectives of experts. To figure out the factors, several questionnaires were distributed among selected experts and their viewpoint were collected and analyzed. Three rounds of survey were performed until the experts reached a consensus on the most important parameters.

3. **Condition Index Model**

   The factors selected in Delphi survey are prioritized and ranked based on their relative importance through integration of two ranking methods of Fuzzy Analytical Hierarchy Process and Shannon Entropy method. Results are employed to estimate the condition of the pipe segments and establish a condition index model.

4. **Remaining Useful Life Model**

This step utilizes artificial neural network to predict remaining useful life of in-service pipelines from their condition and physical properties. Different training algorithms, number of neurons and hidden layers are employed to find the most accurate model which estimates the residual life precisely.

5. **Budget Allocation Model**

This step deals with constrained budget for yearly maintenance plans of the water distribution network. It chooses one scenario for each segment considering the future breakage rate and the relative cost of different scenarios. Genetic algorithm is applied to maximize use of budget through minimizing the difference between total cost and constraint budget.

1.4. Organization of thesis

This research proposal consists of six Chapters as follows:

Chapter 2 covers the literature review. The review focuses on the related aspect of the methodology including: 1) Factors affecting the deterioration, 2) Existing leak detection methods along with their advantages and limitations, 3) Performance models, their basics, input data and results, 4) Selected research techniques, 5) Findings, limitations and research gaps.

Chapter 3 describes the research methodology containing models development, it first defines how condition index is estimated from the parameters selected through Delphi study and ranked by Fuzzy Analytical Hierarchy Process and Shannon Entropy. Then, different steps of predicting remaining useful life are explained. Chapter 3 is wrapped up by demonstrating the budget allocation model.

Chapter 4 explains the data collection and analysis. It expresses how data is collected from literature, questionnaires, municipality of Montreal and the way data is analyzed.

Chapter 5 elaborates the development of the models previously described in chapter 3. It describes each model individually and disclose model implementation to the case study of city of Montreal.

Chapter 6 wraps the study up by highlighting the conclusions and contribution. It also emphasizes on the limitations and brings up a few recommendations for future works.

CHAPTER 2: LITERATURE REVIEW

2.1. Chapter overview

This Chapter aims to provide a comprehensive and thorough literature review about water distribution networks and deterioration models. It starts with a complete explanation about factors influencing failure and deterioration and goes over the entire factors one by one (section 2.2). It continues with describing the current non-destructive leak detection methods classified based on the technologies used and highlights the advantages and drawbacks of each (section 2.3). After that, the existing deterioration and remaining useful models are briefly explained and their inputs and outputs are introduced. Furthermore, the limitations of each class of models are brought out (section 2.4). Next section comes with those research techniques, which were used during this study including Delphi technique, Analytical Hierarchy Process, Shannon Entropy, Artificial Neural Network and Genetic Algorithm (section 2.5). Finally, overall findings and limitation of this review will be demonstrated (section 2.7).

2.2. Factors influencing deterioration

There are several factors in literature which proved to be effective on pipe deterioration. According to National Guide to Sustainable Municipal Infrastructure, these effective factors can be classified as physical, environmental and operational factors. Table 2-1 has summarized all of the factors from Best practice (2003) along with other factors in literature.

Table 2-1.Important factors in deterioration of water pipe (Best practice, 2003)

Factor		Explanation
Physical factors	Pipe material	Pipes made from different materials fail in different ways.
	Pipe wall thickness	Corrosion penetrates thin-walled pipe more quickly.
	Pipe age	Effects of pipe degradation become more apparent over time.
	Pipe vintage	Particular time and place in which pipes are made.
	Pipe diameter	Small diameter pipes are more susceptible to beam failure.
	Pipe lining and coating	Lined and coated pipes are less susceptible to corrosion.
	Pipe installation	Process of installation; Poor installation practices can damage pipes, making them vulnerable to failure.
	Pipe manufacture	Defects in pipe produced by manufacturing errors can make pipes vulnerable to failure. This problem is most common in older pit cast pipes.
	Pipe length	The length of pipe between two sections, the possibility of failure increase with increasing in length.
	Pipe location	Migration of road salt into soil can increase the rate of corrosion.
	Type of joints	Some types of joints have experienced premature failure (e.g., leadite joints).
	Thrust restraint	Restraint to bear longitudinal stresses, Inadequate restraint can increase longitudinal stresses.
	Dissimilar metals	Connection of two pipes with different materials, Dissimilar metals are susceptible to galvanic corrosion.
Environmental factors	Bedding Soil type	Some soils are corrosive; some soils experience significant volume changes in response to moisture change, resulting in changes in pipe loading. Presence of hydrocarbons and solvents in soil may result in some pipe deterioration.
	Backfill material	Some backfill materials are corrosive or frost susceptible.
	Soil pH	Low pH reduces the strength of the PCCP.
	Groundwater	Groundwater can be aggressive toward certain pipe materials.
	Weather/temperature	Climate influences frost penetration and soil moisture. Permafrost must be considered in the North.
	Disturbance	Changes in the support and loading structure on the pipe, Underground disturbances in the immediate vicinity of an existing pipe can lead to actual damage, change in the support and loading structure of the pipe.
	Stray electrical currents	Occurrence of electrical currents between two objects that ideally should not have any, Stray currents cause electrolytic corrosion
	Seismic activity	Seismic activity can increase stress on pipe and cause pressure surge.

	Traffic distribution/ Landuse	Effect of external static and dynamic load on pipes.
Operational factors	Water pressure	Changes to internal water pressure will change stress on the pipe.
	Water quality	Some water is aggressive, promoting corrosion.
	Water pH	Low pH and low alkalinity cause loss in strength.
	Water velocity	Rate of internal corrosion is greater in unlined dead-ended mains.
	Leakage	The leakage rate and size if there is any.
	Backflow potential	Unwanted flow of water in the reverse direction, Cross connections with infrastructure that do not contain potable water can contaminate water distribution system.
	O&M practices	Quality of the performance of operation and maintenance practices.
	Oxygen content	Oxygen helps in corrosion.

All these factors lead to deterioration of pipelines. Several different factors are studied in most of the researches performed on deterioration models. In the next section, each factor is explained briefly where applicable.

2.2.1. Physical/Structural factors

Pipe material: There are variety of materials such as cast iron (CI), ductile iron (DI), stainless steel, asbestos cement, reinforced concrete (RC), pre-stressed concrete cylinder pipe (PCCP), polyethylene (PE), and PVC for pipeline. They can be classified as three main groups of cement-based, plastic and metallic pipes. Each material has its own features, benefits and limitations. Best practice (2003) considered pipe material as an important factor in deterioration process and reported that pipes made of diverse materials fail in different ways. According to AWWSC (2002), cast iron pipes which were prevalent before 1940's, become less popular after 1970's.

Pipe thickness: Røstum (2000) reported that in some cases, older pipes fails less than younger pipes. He believed it is because of the fact that newer pipes have thinner wall thickness. Thin-wall pipes are more susceptible to corrosion and external stress.

Pipe age: As pipe becomes older, it requires more attention and rehabilitation. It is reported that age should be considered along with other factors to assess the condition of the pipe. Many studies showed that annual break rates have direct relation with pipe age and increase with aging. It is believed that pipe age has the most influence on pipe condition (Al-Barqawi and Zayed, 2006; Davis et al., 2007; Wang et al., 2009, 2010)

Pipe length: As the length of a pipe increases, there will be more connections on the pipe and the possibility of confronting a problem throughout the length will grow up as well. On the other hand, longer pipelines are mostly used in rural areas in which the situations are constant while shorter pipelines are used in urban areas where possibility of breakage is higher (Wang, 2006).

Pipe diameter: There are three groups of diameter considering the size: small diameter (50 mm to 200 mm), medium diameter (240 mm to 750 mm) and large diameter (900 mm to 1800 mm). Best practice (2003) has reported that small diameter pipes are more susceptible to failure. Kettler and Goulter (1985) assumed that the relationship between diameter and failure is because of the greater wall thickness of larger diameter pipes. Røstum (2000) reported that high possibility of failure in pipes with diameter less than 200 mm is due to the reduction in pipe strength and wall thickness. He also mentioned that lower velocities of longer pipes result in sedimentation of suspended material and may provide great place for growth of bacteria. Rajani and Makar (2000) and Park and

Loganathan (2002) have shown that deterioration of smaller diameter pipe is faster than larger one because pipe's structural resistance is influenced by size of the corroded area. Rajani and Tesfamariam (2007) proved that level of bedding loss has a great influence on small diameter pipes whereas large diameter mains are affected by external loads. In contrast, since larger pipelines have larger surface, they are more susceptible to corrosion through their contact with soil.

Pipe lining and coating: Lined and coated pipes are less susceptible to corrosion (Best practice, 2003). In some cases, such as asbestos cement corrosion of pipe interior wall leads to release of asbestos fiber in water which is highly detrimental to health (Ossai et al, 2015).

2.2.2. Environmental factors

Soil type/Backfill material: Clay, sand, silt and crushed stone are various types of surrounding soil. This factor is one of the primary factors affecting the structural deterioration through external corrosion. The external corrosion in metallic pipes occurs mostly because of the electrochemical reactions; while cement based pipes deteriorate due to degeneration chemical reactions (Wang, 2006). The surrounding soil and backfill material can be highly aggressive or shrinkable which causes corrosion or breakage.

Groundwater: Watson (2004) reported that groundwater could be deteriorative toward certain pipe materials. Al-Barqawi (2006, 2008) and Fares and Zayed (2010) have considered groundwater level as input data for their performance models.

Traffic distribution/Land use: This parameter is utilized to model the effect of external load on pipe. Pelletier et al. (2003) used land use as a contributing factor in failure. Recent studies such as Vanrenterghem-Raven (2007), Poulton et al. (2009) and Davis et al. (2008) used traffic distribution and daily traffic index instead of land use.

Temperature/Climate: Researchers have observed that breakage rate increases during winter. It is because the pipe tends to contract due to the cold weather and consequently tensions are caused. Sægrov et al. (1999) reported that breakage rate increases in summer because of the drying and shrinkage of the soil. Since pipes are weaker in tension than pressure, failure will happen (Wang, 2006). Likewise, frost travels from surface to deeper part because of the cold weather and causes breakage. Moreover, drought and heavy rain lead to unstable ground condition which results in failure of water mains (Laucelli et al., 2012).

Disturbance: Underground disturbances in the immediate vicinity of an existing pipe can lead to actual damage or change in the support and loading structure on the pipe. Studies show that improper bedding may result in premature pipe failure. Geem et al. (2007) and Wang et al. (2010) studied disturbance as a variable in condition rating.

Soil pH: Rajani and Makar (2000) reported that low pH reduces the strength of the pre-stressed concrete pipes (PCCP). It decreases the pH value of the cement resulting in corrosion of pre-stressing wires.

Soil Redox potential: The redox potential describes the likelihood of an environment to receive electrons and therefore become reduced which results in corrosion. Najjaran et al. (2006) utilized redox potential to find deterioration rate using a fuzzy model.

2.2.3. Operational/Internal factors

Water quality: Water quality is an important factor in condition assessment of pipeline, however; not enough research has been performed to figure out the effect related to this factor. If water quality is aggressive, it increases corrosion (Best practice, 2003). As a way of illustration, aggressiveness index is the best indicator in asbestos cement pipe to check the internal corrosion. After discharging high quality water into network, there is no accurate monitoring system to measure quality reduction of water due to the deterioration. American Chemistry Council (1999) reported that those bio-films growing on pipe interior wall include layers of bacteria which would be attached to the wall and erode internal surface which causes corrosion at the end. Furthermore, coliforms, disinfection by-products, possible presence of copper, lead and iron in raw or finished water lead to slight corrosion and respectively deterioration of the pipeline (Grigg, 2006).

Water velocity: Best practice (2003) specified that rate of internal corrosion is greater in unlined dead-ended mains.

Backflow potential: Cross connections with other infrastructure not containing potable water such as sewers is able to contaminate water distribution system (Best practice, 2003).

Corrosion: In metallic pipelines such as steel, ductile and cast iron, corrosion is a critical factor in pipeline failure. It involves both internal and external corrosion. Internal corrosion is a function of properties of inside water such as pH, bacteria and oxygen contents. On the other hand, external corrosion is governed by soil characteristics such as moisture, electrical resistivity, and pH.

Water pH: Rajani and Kleiner (2001) reported that when asbestos cement (AC) pipe carries water with low pH and low alkalinity, it loses strength and deteriorates. Consequently, asbestos fibers are released and distributed over water network which are detrimental to health. Therefore, lining is necessary to prevent corrosion of pipes due to low water pH.

Cathodic protection: Cathodic protection is used for metallic pipelines such as ductile and cast iron. It decreases the deterioration of water pipelines and it is classified as whether it is applied to water distribution networks or not. The system needs monitoring and frequent inspection and rehabilitation (Gadala et al., 2016)

As can be seen, there are many factors which affect pipeline deterioration and failure in studies. Some of the factors such as pipe age, diameter and material have been considered in most of the studies and there are other factors which have been studied solely in a couple of analysis.

2.3. Leak Detection Methods

Based on the employed technique in the inspection tools, the existing methods are clustered into 4 different categories; (1) visual, (2) electromagnetic and radio frequency, (3) acoustic and vibration, (4) ultrasound techniques. Those that do not belong to one of the identified classes here are grouped under others.

2.3.1. Visual techniques

1. Closed-circuit television (CCTV)

CCTV is a real time assessment technique which is a cheaper and safer alternative to direct human-entry into pipes. It basically comprises a television camera and illuminating appliances mounted on a carrier. It travels through the pipes with help of a winch and pulley system. The operating steps of a CCTV camera are as following; first, the carrier and CCTV are inserted into the pipe via a manhole. Then, the carrier moves along the pipe and the CCTV is set to take pictures and videos of the interior pipe. Afterward, the data will be transmitted to computers (Liu & Kleiner, 2013).

When a leak is observed, the carrier stops allowing CCTV to inspect the area completely. Therefore, the total inspection time of a pipe is directly dependent on the number and size of detected leaks. This makes the CCTV a slow and time consuming method. It gives images of interior surface of pipeline. The problem here is subjectivity of manual interpretation. The operator should detect, judge and classify the leaks. Since his judgment will be affected by his experience, it would be completely subjective. One natural limitation of CCTV is that it is not able to work in water, thus for a comprehensive inspection of the pipe, the pipe interior needs to be emptied and access to pipe is required. Even if the pipe is emptied, limited information will be extracted from images of pipe interior (Hao et al., 2012).

One feasible solution for subjectivity is automatic assessment of images using image processing techniques. Sarshar et al. (2009) proposed semi-automatic software that extracts condition information from CCTV files. Besides, Cherqui et al. (2008) suggested an algorithm for calibrating malfunction indicators based on visual inspection results while

Yang et al. (2011) proposed a quality index of luminance and contrast distortion to improve the accuracy and confidence when compared to original images. Recently, various CCTV cameras are available for different applications in industry. The problem of manual interpretation has not been resolved yet and more efforts are needed for a better level of automation.

2. Laser scan

Laser scan is able to identify the profile of interior side of pipe through the length accurately. This method could also help in finding the corrosion loss and amount of leftovers along with pipe side deflections. This technology consists of a continuous laser beam around the pipe interior which highlights and profiles the pipe at any point of the length only above the waterline. Since there is possibility of laser diffraction in water, this technique is only used during the low-flow times like night or in dewatered pipes. There is no report of underwater laser scanning until today (Liu et al., 2012).

Laser scan basically comprises a spinning apparatus which control the laser beam. There is no need of illumination and the survey could be done in complete darkness. The image resolution is affected by carrier's velocity, speed of spinning, sampling rate, roughness and color of the pipe interior wall. Separate images could be compiled together with pattern and marks on the surface through certain software. By the aid of 3D laser scanning, it is possible to provide 3D profile of the pipe along with 2D images of cross sections (Liu & Kleiner, 2013).

2.3.2. Electromagnetic and radio frequency techniques

1. Magnetic Flux Leakage (MFL)

The MFL method uses magnet to initiate magnetic field around the metallic pipes. Anomalies such as circumferential and longitudinal cracks and corrosions will change the uniform distribution of the magnetic flux. Since damaged areas cannot support magnetic flux as well as undamaged areas, it will be altered in damaged zones. The flux is recorded by magnetic sensors and sensors could detect the perturbation in the field (Liu & Kleiner, 2013).

Figure 2-1.MFL equipment inserted inside the pipe (adopted from www.emtek.us)

Basic principle of MFL is that a pig (pipeline inspection gauge) is inserted into the system, it moves along the pipe and records defects of the interior wall. It is designed to minimize obstruction of the flow and has the ability to detect minor leaks (Costello et al., 2007). Wilson et al. (2008) proposed a pulsed excitation for MFL to acquire more information from wider frequency band. This technique was developed recently to get data about depth of anomalies. Efforts have been made to develop the performance of MFL. EMTEK group has combined different sensors with extra high resolution MFL to conduct a thorough inspection of both internal and external anomalies (Hao et al., 2012).

2. **Eddy current technique**

Eddy current technique is used for small cast iron and steel pipes of less than 10 cm in diameter. In this method, a periodical magnetic field is induced in the pipe. This magnetic field creates electrical currents which produces another magnetic field consequently. The new generated field opposes the main field which results in altering the impedance of the coil. When the coil moves along the pipe, related characteristics will be identified with measuring the impedance (Costello et al., 2007).

Eddy current technique does not require close contact with pipe but there is a problem with wall thickness which affects the induced frequency. Remote field eddy current technique (RFEC) was proposed to ease this problem. This method is based on the fact that the remote field signal is larger than direct eddy current signal and works through the walls. There is an emitter coil inside the pipe and its axis is parallel to the axis of pipe. A pickup detector is also positioned inside the pipe in the distance of 2.5 pipe diameter away from the emitter. (Hao et al., 2012, Costello et al., 2007)

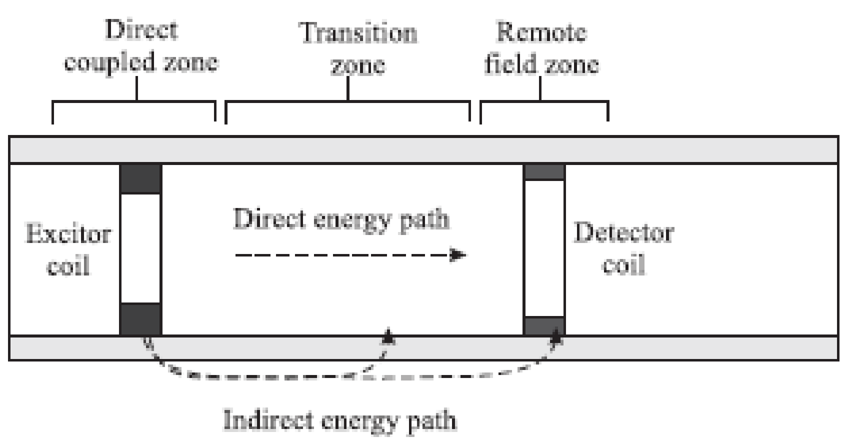


Figure 2-2.Remote eddy current basics (adopted from Liu & Kleiner, 2013)

McDonald and Maker (1996) evaluated the accuracy of RFEC and reported that RFEC is able to detect defects of 3600 mm^2 with precision of ±0.55mm. It is reported that adding extra coil to RFEC makes it more precise. They also proposed a commercial device working under water for 150 mm pipe. RFEC is also used for Pre-stressed concrete cylinder pipes (PCCPs) since they have two metallic elements: a cylinder and a pre-stressing wire. Both metallic elements are involved in magnetic field. Analyzing the results of this technique in PCCPs requires a skilled person which makes the method roughly subjective (Hao et al., 2012).

3. Hydroscope technology

The basic principle of Hydroscope technology is the same as RFEC. In this method, an electromagnetic signal is transmitted through pipe wall. By receiving the signal through a detector and measuring the changes of the electromagnetic signal, this method assesses the pipeline condition. The whole system is inserted into the pipe via an access point and is traveling through the pipe with water flow. This technology is able to inspect 1000 m per day. It was reported those defects less than 3000 mm^2 in size are not detectable in this technique. This method records data every 1.5 mm and transmits it to the field computer through a cable. It is able to work under water, therefore there is no need to empty the pipe. It also covers the limitation of RFEC about lining and is able to test through lining with variable thickness (Hao et al., 2012).

4. Ground Penetrating Radar (GPR)

Ground penetrating radar was first used in 1911 in Germany. This trenchless method is based on transmitting EM waves into ground, receiving back the reflections of underground objects and interpreting them. It is able to identify leaks through detecting voids that have been created by leaking water. GPR system comprises a transmitter and two or three receiving antennas with different frequencies. GPR detects asset location as well as its condition till depth of 5 m. The distance of objects to GPR is computed from the time taken for a pulse to travel back and forth. Although GPR is a real-time assessment technique, it needs a skilled operator to analyze the data. Pulses lose strength quickly while traveling through conductive soils (Costello et al., 2007).

There are different types of GPR named traditional and in-pipe GPR. The traditional GPR is categorized in three groups; time domain, frequency domain and spatial domain. As for in-pipe GPR there are two modes for inspection: look-through and look-out (Hao et al., 2012). In look-out mode, both the transmitter and receiver are inserted inside the pipe while in look-through mode only the transmitter is inserted inside the pipe and the receiver is on the surface. These types of installation prevent EM waves from attenuation through soil. Recently, a new method called Ground Penetrating Imaging Radar (GPIR) has been developed. GPIR creates sharp, 3D images of underground assets with image resolution of less than 50 mm. It detects leaks in all types of pipe material and associated survey velocity is roughly 0.36 km/h (Liu & Kleiner, 2013).

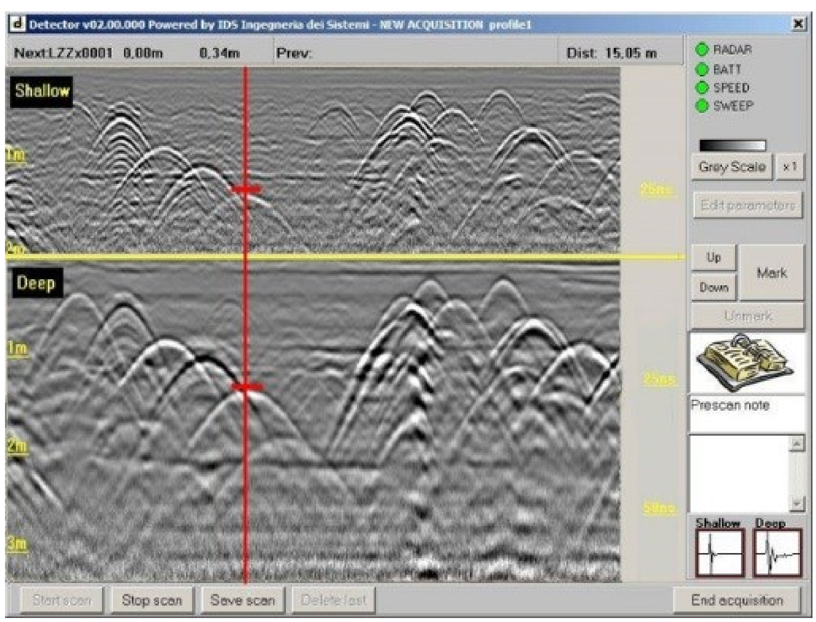


Figure 2-3.GPR result map indicates location of assets (www.edenbros.com)

5. Time domain ultra-wideband (UWB)

Time domain ultra-wideband (UWB) is a condition monitoring method which works in wider range of frequencies and outputs better image resolution. The frequency is in the range of 1000 to several billion in a second (Sachs et al., 2008). Mostly, it is used for leak detection in non-ferrous pipelines. It transmits and receives a pulsation in Pico- or Nano-second to detect voids in soil surrounded the pipe. Results show that UWB system is able to identify slight voids (Hao et al., 2012). Jaganathan et al. (2010) reported that the technique is very accurate since it detects all the characteristics of a defect such as location, size and orientation. It also identifies wall thickness of pipe and detects corrosion. A commercial prototype is still under research and is expected to be available in near future.

6. Broadband electromagnetics (BEM)/Wave impedance probe (WIP)

The WIP technique is a combined technique of GPR and electromagnetic methods. It is based on detecting changes in electromagnetic impedance of the inspected material. It is applicable for all pipes ranging from 0.2 to 5 m in diameter and 0.5 to 10 m in depth except ferrous pipelines. This method is available in both surface and in-pipe systems. Data extracted from received signals must be analyzed after inspection, however, large defects could be detected in field (Hao et al., 2012).

2.3.3. Acoustic and vibration techniques

1. Sonar profiling system

Sonar profiling system is an acoustic method for leak detection which has the advantages of working underwater and measuring the corrosion loss along with volume of debris. It consists of a scanner unit, skid set, sonar siphon float, processor unit and cables. The theory behind this system is that it measures the time takes for a sound signal to travel from a transmitter to the target and back. Having this time and speed of sound in travelling medium, the distance between the target and transmitter is calculated. The velocity of sonar signal is approximately 0.1-0.2 m/s and the rate of signal transmitting is one per 1.5 seconds. Every received signal has data about specific cross-section of pipe. Since the velocity of sound is different in water and air, it is not able to work simultaneously in both air and water. Therefore, the images of the sections should be taken separately and be merged at the end of inspection (Costello et al., 2007).

Sonar profiling system uses different frequencies for various applications. For better resolution, it operates with high frequency and for higher penetration, low frequency is employed. Consequently, the problem for low frequency is poor image quality and for high frequency is low penetration. Small leaks and clear water condition are favorable for high frequency pulses whereas low frequency is appropriate in turbid water. Therefore, a multi-frequency system gains the best information (Liu & Kleiner, 2013). Recently, researchers are working on a system comprises a sensor. This sensor is inserted into the pipe from manhole and covers a wide range of frequencies. Then, it starts transmitting signals along the pipe length and receiving them back. There is also a processing unit which estimates the cross section changes in pipe. This system is reported to be efficient in comparison to visual techniques and is more economical since the associated cost is a function of pipe diameter (Hao et al., 2012).

2. LeakFinderRT

A newly developed LeakfinderRT system consists of a range of acoustic sensors such as an accelerometer, hydrophone, wireless signal transmitter and computer. These sensors are installed in two different access points such as fire hydrant or manhole. The basic principle used in this system is cross-correlation function. Cross-correlation function is a measure of similarity of two waveforms when a time-lag function applied to one of them. The computer used this function to calculate the time lag (τ_{max}) between two sensors. The equations related to this method are (Liu et al., 2012):

$$L_1 = \frac{D - c\tau_{max}}{2} \qquad 2.1$$

$$L_2 = D - L_1 \qquad 2.2$$

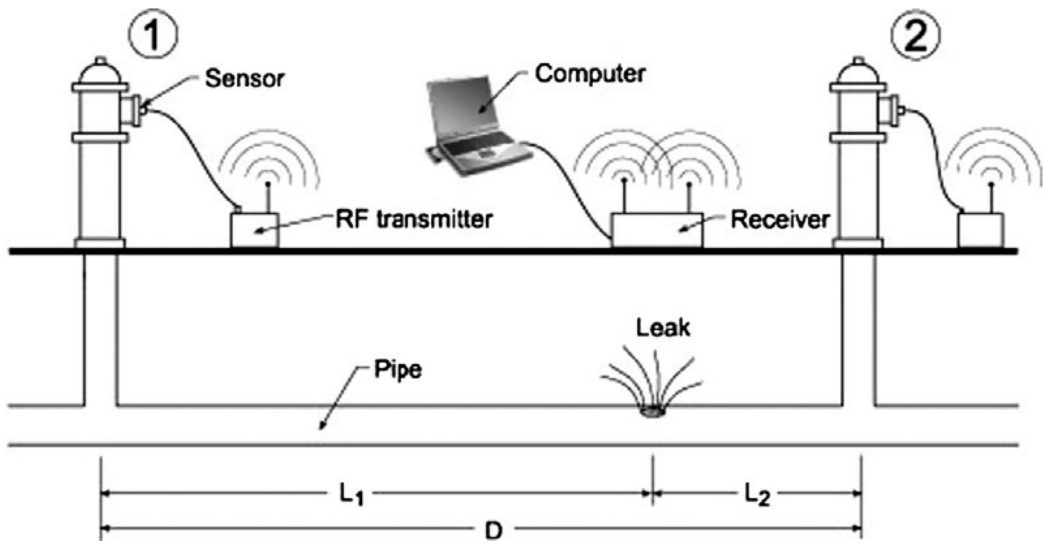


Figure 2-4.Principle of LeakfinderRT (adopted from Liu & Kleiner, 2013)

c is the propagation velocity of sound in the pipe and is determined experimentally. D is the distance between two access points. L_1 and L_2 are positions of the leak respect to the access points and are calculated from the equations above. Leak sounds are recorded and analyzed in a few minutes. In case of background noise, it takes more time to analyze the data. This method which gives improved resolution image of narrow-band leak signals, is not applicable in discontinuity and is not able to find the leak size (Liu & Kleiner, 2013).

3. Sahara System

Sahara system is a sensitive leak detection method consists of a hydrophone, sensor, cables and locator. To record noise, the sensor is inserted into the pipeline with a parachute which helps in moving with flow. The sensor is connected with cable to the surface and transmits data simultaneously and gives real time result. There is also a locator above the surface which is connected to the sensor and tracks and locates leaks exactly for further excavations (Costello et al., 2007).

If a pipeline passes through an environmental obstacle such as rivers or municipal construction like highways, the operator is not able to detect leaks on the ground. Consequently, there should be some adjustments for the system to locate defects on the ground correctly. Recent Sahara systems have video and lighting sensors for more accuracy inside the pipe. This technique is non-destructive, since it uses existing taps of 5 cm to enter pipe. The method is very accurate and sensitive that is able to detect small leaks of 0.005 gpm. It works in all pipelines irrespective their size and material (Liu & Kleiner, 2013). The procedure of this technique is illustrated in Figure 2-5.

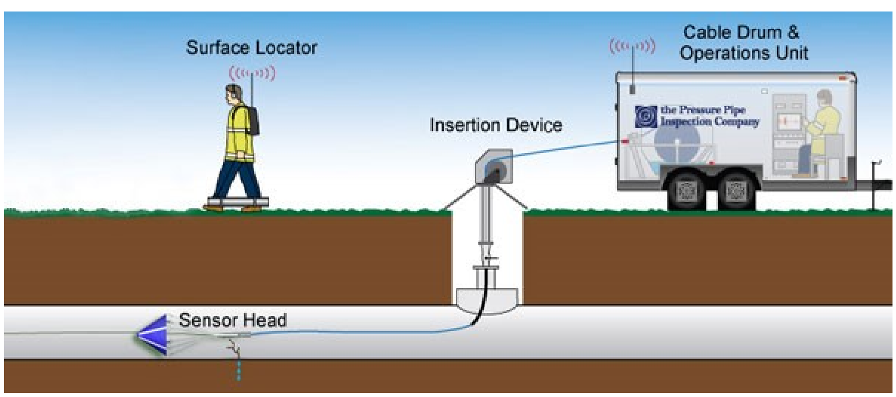


Figure 2-5.Sahara leak detection technique (adopted from www.puretechltd.com)

4. Impact echo

This technique is mainly used for structural condition assessment of pre-stressed concrete pipes. It is developed based on the waves transmitted through pipe and their reflection. It comprises a system generating waves from set of controlled impacts and geophones (Costello et al., 2007). The equation behind the impact echo is $T = \frac{V}{2F_p}$ in which T is thickness, V is wave velocity and F_p is peak frequency. This equation is computed between the transmitter and receiver. The system transmits waves through wall, then reflected waves with different speeds, frequencies and rates of penetration are recognized by geophones. The outputs give information about overall condition of the pipe. This method is applicable to all pipe size (Liu & Kleiner, 2013).

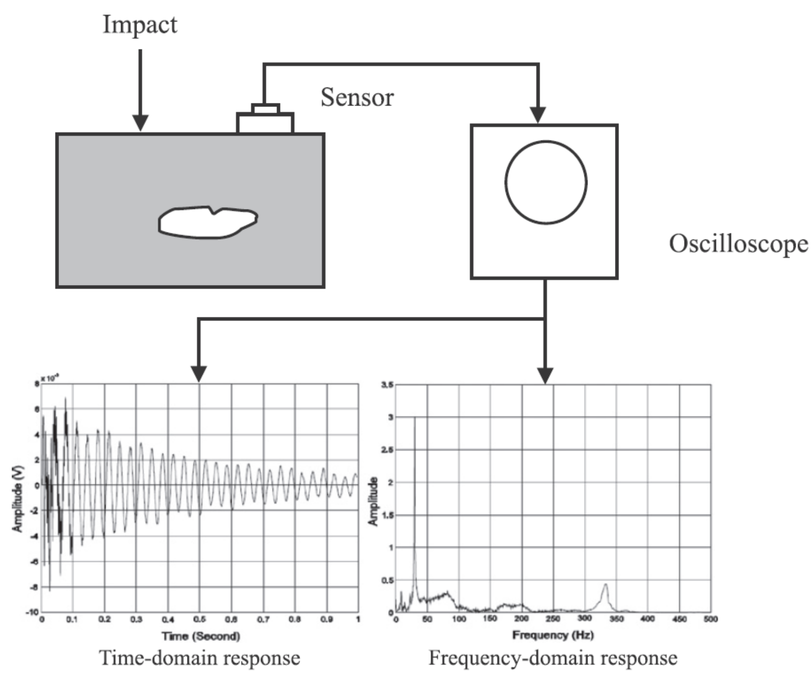


Figure 2-6.Basic principle of Impact echo (adopted from Liu & Kleiner, 2013)

5. Smartball

Smartball is a recently-developed leak detection tool which consists of a range of sensors such as magnetometer, ultrasonic transmitter, accelerometer, temperature sensors and power source. All the sensors are encased in a core which is inside an outer shell. This shell protects the core and eliminates generated noises from penetrating inside the pipe. The diameter of Smartball is normally less than one-third of the pipe diameter; however, it should meet the limitations of size of valves and accessories which it is inserted through and exited from. Smartball is able to travel and collect information through pipelines for up to 12 hours. It is inserted into the water pipeline via an access point and moves towards the pipeline while transmitting and recording sound every 3s. The receiver sensor is used to find the location of the Smartball by analyzing the arrival time of the acoustic signal. The recorded data are analyzed to locate the leaks with 1 m of accuracy (Liu et al., 2012).

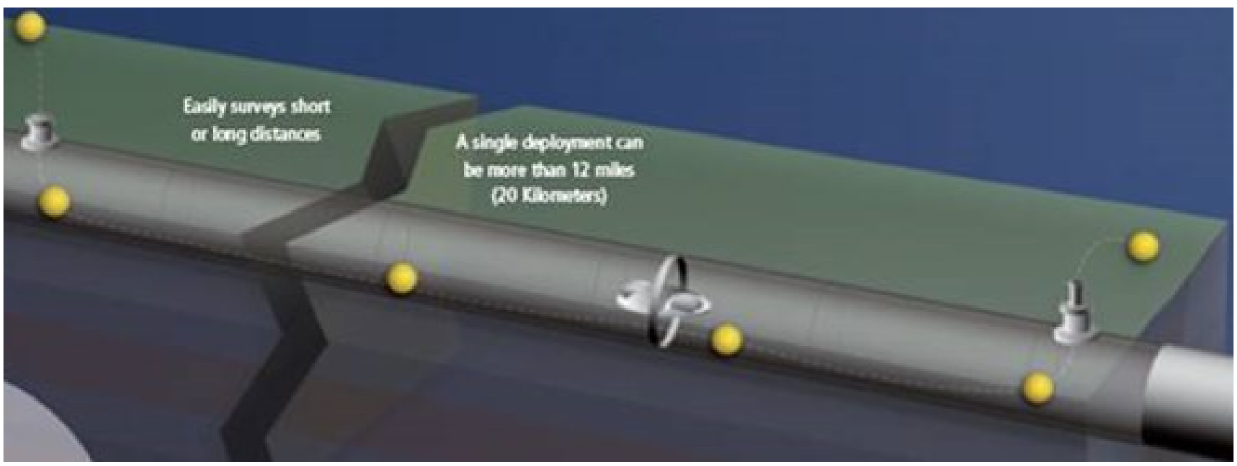


Figure 2-7.Smartball deployment and recovery (adopted from rebar.ecn.purdue.edu)

6. **Correlator and listening stick for leaks**

This method is mostly used in suspected areas. The sticks are used near the assumed leak for listening to the sounds and calculating time delay based on the sound speed in the pipe. This method is mostly used in metallic pipes and is not good for plastic pipes. Also, access to pipe is required (Hao et al., 2012).

2.3.4. Ultrasound techniques

1. Guided wave

This method is based on propagation of wave through pipeline. When the guided waves confront an anomaly, they will reflect back to transducers. Time for each sign of anomaly is used to calculate the distance to the transducer. The amplitude of the sign is used to determine size of the leak. There are two kinds of wave; torsional and longitudinal. Torsional wave moves with a shearing motion, attenuates less by water and coatings, requires two transducers operating in pulse-echo configuration, and works in in-service pipes.

Longitudinal wave travels via compressional motion and needs three to four transducers. It uses three transducers for a single frequency wave while multi-frequency waves are generated when four transducers are used. This improves the quality of inspection results. The technique is applicable in situations where diameter is more than 50 mm and wall thickness is less than 40 mm. This method is able to detect corrosion and needs access to pipes (Liu et al., 2012).

2. Discrete ultrasound

A discrete ultrasound system comprises a transmitter/receiver, transducer and monitor. The transmitter transmits a pulse and the transducer produces a high-frequency ultrasonic energy wave which moves through pipe. When this energy wave encounters an anomaly, portion of energy will be reflected back and reconstructed into an electrical signal. It holds data about size, location and other features of the anomaly. The results are given in three different view of cross-section, Plainview and side view. The time taken up by the pulse to travel forth and back is used with wave speed to calculate the distance of the defect from the transmitter. This inspection is performed both internally and externally and is accurate; however, waves need water or a material to propagate through it (Liu & Kleiner, 2013).

3. Phased array technology

This technique uses an arrangement of sensors which are individually set and ready to be used. The sensors could be formed in different state which are called virtual sensors. It is easy to program a virtual sensor to transmit sound beams with different apertures, shapes and directions. e.g., a virtual crack detection sensor is including a group of sensors which transmit waves with definite time shift from sensor to sensor (Liu & Kleiner, 2013). The ability on clarifying complicated defects such as cracks, metal losses or hook cracks is a major benefit of this technique. It detects discontinuity and requires less time to analyze data. Although this technique is commercially available, but there is no evidence of its application in water mains (Liu et al., 2012).

4. Combined ultrasound inspection

This technique detects crack and identifies metal loss at the same time. It employs innovative and optimized sensors to perform both inspections at a same time. The sensors work in pulse-echo mode to perform high repetition frequencies (Liu & Kleiner, 2013). This technique was first developed for oil and gas pipelines; however, it is applicable in water pipe as well. The only problem is that this technique needs access to pipe to perform the test.

2.3.5. Other techniques

1. Radiographic methods

Radiographic technique uses Gamma or X-rays to radiate through pipe materials. The radiations pass through the material and affect a photographic film on the opposite side of the pipe. Changes on the film show possibility of defect. There are three different setups for this method; single wall-single image, double wall-single image and double loading. Those defects that can be identified are pits in cementitious material, inclusions and corrosion in metallic pipes. Gamma ray is used for metallic and concrete pipes whereas X-ray is applicable in plastic pipes. This method is accurate; however, pipes with diameter more than 38.1 cm should be emptied (Liu & Kleiner, 2013).

2. Infrared thermography

Infrared thermography is based on the energy transfer theory i.e. energy circulates from warmer to cooler places. Any object above -273 °C (0 °K) radiates infrared energy. The amount of radiated energy is a function of temperature and emissivity (Hao et al., 2012). Infrared thermography system consists of an infrared scanner and a camera. The scanner measures temperature changes and produces thermographic images. When a defect happens in pipe, the water starts passing through the pipe wall inside the soil, which causes a decrease in temperature of the surrounding soil (Zangenehmadar and Moselhi, 2015). Sometimes, the system includes an external heat source to reheat the objects. Therefore, cooling characteristics are scanned and images are produced based on them. Infrared thermography is sensitive, reliable and accurate and needs minimum instrumentations since it is trenchless. The major problem is its failure to measure the depth and the size of the leak because different soil types and pipe materials have various amount of energy.

Ground cover, moisture content and wind speed are reported to influence the results (Liu et al., 2012).

3. Continuous wave Doppler sensing technique

This system is made up of a 2.45 GHz-continuous wave doppler sensing unit, transmitter, receiver and a digital signal processing unit. The sensing unit sends a signal and receives the reflection which has been shifted through water that leaks out. This method works in all environmental condition, soil types and pipe materials. It detects and locates all the leakage points accurately. The method is expected to work along with other leak detection methods to provide comprehensive inspection results for water leak detection. One problem is the medium speed of inspection; it takes more than 3 minute to identify a leak. also the depth is between 1 to 2 meters. Researches are ongoing to improve the inspection speed.

4. Acoustic fiber optics

This method consists of fiber optic sensors located along the length of the pipe and are connected to an optical data obtaining system. The optical data obtaining system has a laser which produces a light through the fiber. Acoustic wave imposes stress on the fiber; which causes reflection in the light through the fiber. This reflection is analyzed by data obtaining system and the outcome is inspection data. The system is susceptible to physical damages and special test equipment is often required for installation which makes it costly. However, this method is used when early detection of leaks is more essential than the cost.

2.3.6. Summary

As pipelines deteriorate, they are more exposed to failure from internal and/or external causes. Failure causes leakage and affects water quality. This section reviewed 22 methods of leak detection. These methods were grouped in 5 classes of visual, ultrasound, electromagnetic and radio frequency, acoustic and other. Visual methods frequently need pipe to be dewatered and require an experienced operator to interpret the images. This limits their usage in inspection. Acoustic methods get access to pipe through fire hydrant for inserting the sensors. They are the most commonly used methods among the 5 classes because of their relatively lower costs and more user-friendly systems. Sahara system and Smartball provide exact data about leak size and location, however their cost of inspection is relatively high (vary between 14 to 17 thousand dollars per kilometer) comparing to the cost of the LeakfinderRT system which is $25 000; excluding labor cost.

Electromagnetic and radio frequency methods except GPR are only applicable in metallic pipelines. Eddy current technique and MFL are good for small pipes while hydroscope technology and RMPS are able to detect defects in large metallic pipes. In this category, only GPR detects defect during inspection independent of pipe material and size. Ultrasound methods detect corrosion and metal loss in addition to leakage. The cost of some of the methods are summarized in Table 2-2. The diverse limitations and capabilities of the methods presented in this Chapter calls for joint use of more than one method for efficient inspection as in the proposed two tiers inspection method in Zangenehmadar and Moselhi (2014).

Table 2-2. Cost of different leak detection methods

Method	Type	Cost ($)	Company	comments
GPR	Radiodetection RD100	8,700	Opti-cal	
	oko-2 (central processing)	22,450	accurate locators	
	oko-2 (antenna AB-400)	7,330		
	oko-2 (antenna AB-1700)	8,020		
	oko-2 (ABDL triton)	8,591		
	oko-2 (transportation + displacement)	1,250		
	Zond (Control unit + software)	15,026	accurate locators	
	Zond (Antenna system)	3,980		
	Zond (100 MHZ Antenna)	6,280		
	Zond (300 MHZ Antenna)	2,892		
	daily	10-50	Tecterra	
	weekly	10-250		
	monthly	50-1,020		
	GPR sencion	30,000-50,000	Sencion	
	radioteam cobra locator (new)	17,750		
	radioteam cobra locator (used)	16,350		
Sahara/ Smartball	mobilization and demobilization	20,000-30,000	pure technologies	
	project planning and site review	5,000-10,000		
	inspection fee / km	10,000		
	written report fee	7,500		
Infrared thermography	Thermal camera	10,000-50,000	Inspectahire	200 $/km + 120 $/km labour cost
	Thermal camera	40,000	Adept marketing	
Acoustic	leak noise correlator	18,000	Gutermann	
	aquascan TM	30,000	Gutermann	
	aquascope 3	3,400	Gutermann	
	aquaphon	9,084	SEWERIN	surveying 75-100$/km
	Aquatest T10	3,150	SEWERIN	
	secorrphon AC06	20,744	SEWERIN	
	secorr 08	13,360	SEWERIN	
	secorr 460	7,400	SEWERIN	
	LeakfinderRT	25,000	echologics	50 $/km + 100 $/km labour cost

2.4. Existing performance models

Proposing a generalized and reliable performance model to be used in all conditions is very difficult and maybe impossible. The existing water pipe condition, deterioration and failure rate models are grouped in 5 different classes of deterministic, statistical and probabilistic, artificial neural network, heuristic and fuzzy logic models. The following section will present the inputs, the methodology used and the expected outputs of the models.

2.4.1. Deterministic Models

Deterministic models are mostly used in the situations where there is a real relationship between parameters. They could be subdivided into empirical and mechanistic models. Empirical models relate the rate of failure to characteristics of a network of pipes while mechanistic models are applicable in Predicting the service life of individual pipes. They mainly involve the use of laboratory tests and specimens to obtain required information.

Rajani and Kleiner (2001) performed a comprehensive review about structural deterioration of water mains concentrating on “physically-based” models published until 2000. They reviewed physical deterministic models of Doleac et al (1980), Kumae et al. (1984), Randall-smith et al. (1992), and Rajani and Makar (2000). Rajani and Makar (2000) proposed a methodology to estimate the residual life of grey cast iron water mains. They evaluated the effect of corrosion on pipelines. They measured corrosion pit, residual resistance capacity and calculated corrosion rates to forecast the time takes for Factor of Safety (FS) to become less than minimum threshold. The remaining service life is used to arrange maintenance and replacement scenarios for water mains. To estimate the residual resistance capacity, sample pipe sections are analyzed and data about several features of pipe and soil is collected. The collected information comprises of pipe components (pipe diameter, laying condition and depth, wall thickness, installation year, age, bursting tensile strength, tensile strength, ring rupture modules and fracture toughness). It also contains the soil components (soil pH and soil resistivity, backfill material and backfill weight density) and operational components (pressure, surge pressure allowance, water temperature, frost load factor, impact traffic factor, wheel load, and traffic reduction factor).

Deb (2002) presented a model which prioritizes water mains replacement and rehabilitation in cast iron pipes considering the increase in corrosion pits and reduction in pipe strength over time. The inputs which were extracted from sample sections of the pipe, are pipe components (material, diameter, length, depth, and installation year), soil class, traffic type, working pressure, pavement type and beam span. This model determines maximum loads applied to the mains and assesses the residual strength of the pipe. Afterwards, it arranges the water mains for replacement or repair based on the calculated Factor of Safety (FS) determined for each pipe section. FS is residual strength of the pipe as a function of remaining wall thickness divided by maximum stress subject to the pipe. The proposed methodology relates pipe wall thickness to module of rupture, tensile strength, ring module, and fracture toughness. In this model, soil type proved to be the most effective factor in estimating the FS since the methodology is concentrating solely on external corrosion caused by corrosive soil.

Babovic et al. (2002) proposed a data mining method to model water supply assets. They used ranking models and Bayesian networks to assess the risk of pipe bursts. In general, ranking models are used to demonstrate relationships between inputs and outputs. In this model, one score is assigned to each case and cases with similar score are grouped together.

Then cases in which pipe breakage has occurred are counted respect to total. In parallel, Bayesian networks incorporated uncertainties into data with graphical models. Comparing these two data mining methods, it could be concluded that ranking models provided lower maximum failure risk and were able to classify more cases. The inputs of ranking model are pipe diameter, length, material and age, number of bursts, number of houses where the pipe starts and ends, and the traffic frequency. Another problem for ranking method is that it is driven from data and the accuracy of the models depends on the quality of data, while Bayesian networks use theoretical knowledge in addition to data. Input parameters for Bayesian network are pipe depth, material, mean diameter, thickness, age, installation method, age of last burst, previous repairs, rainfall, temperature, and soil type. This study is solely a preliminary study about these data mining models and needs further investigations.

Lu et al. (2003) presented a model which predicts lifetime of acrylonitrile-butadiene-styrene (ABS) plastic pipes subject to deflection loading and combined pressure. The model utilizes linear fracture mechanics technique to investigate brittle failure in order to predict the service lifetime. In this technique, stress intensity factors (SIF) are linked with pressure, deflection and residual stress. Their combination is used to determine the net total stress. To predict lifetime of water mains, a time marching loop is used. The loop is repeated simulating crack growth until the SIF becomes equal to current fracture toughness of the ABS material. The limitation is that this model should consider parameters such as pipe diameter, thickness and internal pressure for prediction. Factors of soil deflection, initial flaw size, fracture toughness, slow crack growth resistance and residual stress, which control the pipe life, were measured through the analysis.

Farshad (2004) presented two new criteria of ultimate strain extrapolation method (USEM) and the distortion energy extrapolation method (DEEM) for service life prediction. Both criteria entail internal hydrostatic pressure test and creep test to evaluate time-dependent creep modules and hoop stress. The USEM and DEEM are calculated from the relationships between evaluated factors with strain distortion energy. Results were compared using a classical standard extrapolation method with USEM and DEEM and was satisfactory. DEEM is valid for wider ranges while USEM is appropriate for materials which fail under ultimate strained state instead of maximum stress. A case study of PVS-U pipe is used for verification of the model.

Seica and Packer (2004) proposed a finite element evaluation of the remaining mechanical strength of deteriorated cast iron pipe which is able to predict the strength based on longitudinal bending. This finite element evaluation is similar to the simplified numerical method presented by the authors in another article (Seica and Packer, 2006). The assumption in the model is that the pipes experience uniform or no corrosion. In order to employ cross section analysis to compare the results, the pipe was divided into cross sections. Wall thickness and internal diameter were measured to calculate the amount of material loss due to the corrosion. Comparing the outcomes of cross section analysis and finite element evaluation, it can be seen that the results are approximately similar. In special cases, section analysis method overestimates the strength of pipe in comparison to finite element method. Cross section analysis is not accurate since it utilizes smear approach. Other inputs of the model are tensile stress and strain.

After Seica and Packer, Kim et al. (2007) presented two methodologies of assessing fracture toughness and residual tensile strength of cast iron pipes to predict residual life.

They used some specimens and measured characteristics of nominal diameter, width, gross thickness, pit depth, metallic thickness, breaking loads and geometric factor. Fracture toughness methodology used FS for structural stability, while tensile strength methodology uses statistical analysis for mechanical intensity and characteristics of corrosion pits. The outputs of both models are satisfactory in residual life prediction; however, fracture toughness analysis is more reliable.

Davis et al. (2008) also investigated fracture prediction in five types of polyethylene (PE) pipes using measured craze strength versus failure time to predict exact time of crack initiation under pressure and deflection load. Comparing the results of the predicted model with actual observations, it can be seen that model underestimates the failure time. The model is good at predicting crack initiation time; however, it is not helpful afterwards. The inputs are specifications of the sample specimens such as diameter, thickness, pressure, deflection, initial crack length, actual and predicted failure time. The authors also proposed a model for long term performance and lifetime prediction based on craze mechanics for PE pipes (Davis et al., 2007).

Burn et al. (2009) did a complete research about three models used in risk analysis of pipeline assets. He examined application of linear elastic fracture mechanics (LEFM), elasto-plastic fracture mechanics (EPFM) and craze mechanics for failure prediction in plastics pipeline. The LFEM theory considers stress intensity factors and toughness of the pipe material and calculates fracture process. The second theory is used for crack blunting and non-linearity in material deformation. Craze mechanics measures the stress in a material. Results show that a large craze zone is formed at crack tip and LFEM and EPFM are not applicable. It should be noted that more investigations and sample specimens are yet necessary to validate the results of the craze mechanics method.

As can be seen from deterministic models, most of the models are not generalized. They are mainly applicable in cast iron and plastic pipes and require sample specimens of pipe for verification which is a difficult data to acquire. Since deterministic models are simple in nature, they are not suitable to account for nonlinearity in behavior of soil and pipe materials such as corrosion and stress. Deterministic models are site-specific since applicability of each model is restricted to a certain location and related factors.

2.4.2. Statistical and Probabilistic models

Statistical and Probabilistic models are commonly used to predict service lifetime of assets and likelihood of occurrence of an event. Data about condition and features of pipes are necessary to generate expected outcome through statistical analysis. Therefore, large and long term historical databases are required.

Kleiner and Rajani (2001) made a comprehensive review of statistical and probabilistic models about structural deterioration of water mains until 2000. They divided the models into four categories based on the approach of problem solving. It includes time-exponential models (Shamir and Howard, 1979; Walski and Pelliccia, 1982; Clark et al., 1982), time-linear models (McMullen, 1982; Kettler and Goulter, 1985; Jacobs and Karney, 1994), Probabilistic multi-variate models, proportional hazards and accelerated life (Marks et al., 1985; Andreou et al., 1987; Marks et al., 1987; Bremond, 1997; Constantine and Darroch, 1993; Miller, 1993; Constantine et al., 1996; Lei, 1997; Eisenbeis et al., 1999) and

Probabilistic single-variate group models (Kulkarni et al., 1986; Goulter et al., 1993; Deb et al., 1996; Mavin, 1996; Herz, 1998; Gustafson and Clancy, 1999).

Le Gat and Eisenbeis (2000) used maintenance records to forecast failures in water networks in different materials. They calculated the times and number of failure using Weibull Proportional Hazard Model (WPHM). The survival function considered the factors affecting the failure of the pipe. The model used two databases to check both observed and predicted failures. It underestimated one of the case studies because of the increased pipe deterioration and lack of data. Moreover, there is no evidence of model validation in this study. Factors considered in this study are Pipe components (length, age, diameter, pressure and material), soil type, traffic load, and supply method such as gravity and pumping. History of previous failures was taken into account for calculation.

Park and Loganathan (2002) proposed a methodology for efficient optimal replacement of pipes in water distribution systems. The method uses threshold break rates and failure prediction models to determine the time. They considered the optimal threshold break rate as a function of pipe diameter and costs of replacement or repair. By setting the threshold break rate equal to estimated rate by failure prediction model, the replacement time is calculated. The inputs of the model are number of breaks per 1000 ft of pipe, growth rate coefficient, annual interest rate, repair, and replacement costs for the pipe length. In addition, Loganathan et al. (2002) proposed a threshold break rate for pipeline replacement in water distribution systems.

Pelletier et al. (2003) Modeled water pipe break rates based on breakage history and pipe components (diameter, length, material and age). The authors estimated present and future structural states of water main by use of pipe break model. Statistical functions of survival, probability distribution and hazard were utilized to represent the Weibull and exponential distributions. Three case studies were performed to analyze the model. The survival functions were versus time and they are based on the Weibull distribution of the pipe failure through pipe age. Results show that material and installation method affect pipe deterioration. This model does not take into account the corrosion and leakage. It only considers breaks due to natural aging of pipes. Other inputs of the model are soil type and land use.

DeSilva et al. (2006) proposed a condition assessment and probabilistic analysis to estimate failure rates in buried metallic pipeline. Most of the water networks confront the problem of data scarcity since there is no complete database about breaks history of water mains. Therefore, condition assessment is used to find the deterioration rates and probabilities of failure in a distribution system. First, a Weibull probability distribution function is used to estimate maximum corrosion rate. Then, the distribution is extrapolated over larger target area. After that, it is converted to corresponding normal distribution functions. Later, the probability of failure was determined using first-order-second-moment analysis. In validation, results of binomial probability process show the relationship between failure rate and time. Overall, the model entails prediction of failure of entire pipeline assessing condition of selected sections. The model takes into account variables of maximum applied stress, critical stress required for failure related to external and internal galvanic corrosion, internal pressure, pipe wall thickness and radius of the pipe.

Vanrenterghem-Raven (2007) proposed a proportional hazard model (PHM) to measure risk factors of structural degradation and break rates of water distribution system through running PHM while one variable at a time is considered. PHM is a statistical method applicable for renewable processes. This methodology calculates expected breaks per pipe using hazard rate. Inputs required for this model is pipe components (length, material (steel/non-steel), diameter and age) and environmental factors (traffic, location, water zones and highways).

Davis et al. (2007) proposed a physical probabilistic model to predict failure rates in buried PVC pipeline. The model used internal defects resulting from internal pressure to determine failure rate. The output of the model was compared to the observed data form different municipalities in United Kingdom. Results show that predicted curves are in a favorable agreement with observed data. A Monte Carlo simulation estimates the lifetime probability distribution. Variables used in Monte Carlo simulation are number of segments, length, incremental time period, material short-term properties (fracture toughness, yield strength and Young's modulus), slow crack growth parameters, visco-elastic parameter for reduction in Young's modulus, outer and inner pipe diameter, maximum internal pressure in each segment, soil properties (cover depth, unit weight and modulus), surface load and residual hoop stress.

Poulton et al. (2009) measured the impact of pipe length on break predictions in water mains. They utilized Linearly Extended Yule Process (LEYP) to find break predictions for each segment. Calculations were done based on intensity function and by aid of LEYP. Intensity function depends on age in the form of Weibull model, number of previous events in the form of LEYP and vector of covariates in the form of Cox proportional hazard model. After model verification, results show that model is not sensitive to small segments, which means that pipe length does not affect breaks since it is merely related to pipe age, water pressure and soil type. Input parameters are pipe diameter, length, installation year, soil type, traffic level, water pressure, type of accident, and date of intervention.

Dehghan et al. (2008) presented a parametric model using probabilistic analysis of structural failure of water pipes. Due to the fact that the theoretical failure rates do not depend on time, the authors tested the steadiness of the failure rates. Results of parametric models are valid when failure rate is considered as a stationary random process. Verification of the model through a case study showed that variables should be updated to represent time dependent nature of failure process. The input parameters are pipe material, diameter and location. Developing a nonparametric model was proposed to investigate the time dependent failure process correctly.

Dehghan et al. (2008) also proposed a nonparametric methodology for Probabilistic failure prediction for pipeline deterioration. The nonparametric methodology considers those factors that are not constant in reality. In this method, probability of failure was estimated by maximum likelihood in order to evaluate number of failure per time and confidence intervals. The methodology was tested through the observed data of water network in Australia. Results show a good agreement between observed and predicted data. As the model doesn’t intend to predict single component failure, mains are analyzed in groups taking into account their material type, diameter, and location.

Davis and Marlow (2008) proposed a physical probabilistic failure model utilizing Weibull probability distribution for quantifying economic lifetime for asset management of large diameter cast iron pipelines. Since enough data about failure was not available, condition assessment was employed to determine remaining life time. To determine the corrosion rate, the model investigated selected parts of the pipe. This model evaluates failure time and economic life time. It only shows longitudinal fracture because it solely calculates internal pressure and in-plane bending. Inputs are pipe diameter, age, thickness, external loads from soil and surface loads, maximum corrosion rate and tensile strength.

Kleiner and Rajani (2008) checked prioritizing individual water mains for renewal using non-homogenous Poisson model. They divided the input parameters of pipe material, diameter, length, installation year, climate, X-Y coordinates of pipe nodes, break date, and type into 3 classes of pipe dependent, time dependent and pipe-time dependent. The model was first trained using maximum likelihood method with a Lipschitz Global Optimizer (LGO) algorithm. Then it was validated by forecasting the number of breaks in a validation period. Afterward, the observed and predicted failures are compared. Results show that model is appropriate and is able to analyze the covariates at group and pipe level.

Davis et al. (2008) presented failure prediction and optimal scheduling of replacement in asbestos cement (AC) water pipes through probabilistic failure model. This model utilizes residual strength to find the deterioration rate employing Weibull distribution. However since there were some differences between data produced and observed, Hertz distribution was employed to model the uncertainty. Results of the verification show that predicted life time using Hertz distribution are similar to empirical lifetime evaluated by Monte Carlo simulation. The data requirements in this article are pipe diameter, thickness, depth, age, internal pressure, unit weight of the surrounding soil, dynamic traffic load, and deterioration rate.

Berardi et al. (2008) suggested using EPR in developing deterioration models for water distribution systems. EPR is divided into two steps: searching for the best model structures using GA and parameter estimation for an assumed structure using least squares method.

EPR performs a multi-objective search to find the best model. Savic (2009) also used same methodology and case study in his article “The Use of Data Driven Methodologies for Prediction of Water and Wastewater Asset Failure”. Since it is not possible to use EPR for direct calculation of failure rate, two different processes were used to find a pipe condition. The processes were developing general failure model and implementing multi-objective approach for pipe rehabilitation planning. Data requirements for model development are pipe parameters of age, diameter, length and number of properties.

Moglia et al. (2008) checked the strong exploration of a cast iron pipe failure model. The first proposed model was improved through several assumptions i.e. time dependent corrosion rates; stochastic pipe wall thickness; stochastic loads; and lower limit on the tensile strength. The new model determines maximum corrosion rates through evaluating the nominal tensile strength. In this model, only failures caused by corrosion or fractures are considered. Since the model has numerous assumptions, it is not generalized. After validation, the predicted and observed data were similar. The input parameters for this model are pipe components (thickness, age, failure and installation year, diameter and length), internal pressure, external and soil load, failure exposure, corrosion rate, number of observed failures and the tensile strength of the pipe samples.

Wang et al. (2009) developed deterioration model to predict annual break rates of water mains respect to pipe material. The method consisted of finding the best subset regression to determine the best relationship between failure rate and variables such as pipe age, diameter and length. In addition to variables mentioned, break records, pipe depth and material are considered. The model was verified using a case study in Canada. Sensitivity analysis was performed to find the ways that different variables affect the annual breaks.

The regression models were verified by F-test and t-test. The model doesn't consider repair history, cathodic protection and soil condition and is not able to predict the next failure.

Wood and Lence (2009) used water main break data to improve asset management for small and medium utilities. Time-linear and time-exponential equations were developed. Results show that with the exception of cast iron (CI), predictions in asbestos cement (AC) and ductile iron (DI) are more accurate utilizing the time-linear equation. Required input data includes break history, ground surface material, pipe material, diameter and age.

Wang et al. (2010) proposed an assessment model of water pipe condition using Bayesian inference. In this model, the relative effects of each factors on model performance was evaluated and those with smallest effect was excluded. Comparing the model output and observed data, pipe age and diameter proved to have the most effect on pipe condition. Verification of model shows that proposed model is within good compliance. Input variables are pipe components (diameter, age, material, depth, inner and outer coating), pressure head, number of road lanes, electric recharge, bedding and soil conditions.

As can be seen from statistical and probabilistic models, statistical models needs large number of long term observed field data while probabilistic models are convenient for databases that have little information. In most of the probabilistic models, condition assessment of a pipe is only analyzed for a pipe section not the entire pipeline. These models only predict the failure of a water pipe and there is no generalization of them.

2.4.3. Artificial Neural Network models

Artificial Neural Network (ANN) models are used to predict pipe failure and condition rating of the pipeline system. Same as previous models, this methodology is not generalized and is unable to predict future failure rates for other areas. Only a couple of the several articles about utilizing ANN in water networks are presented in this study.

Christodoulou et al. (2003) proposed a risk analysis framework for evaluating structural degradation of water mains in urban settings, using neuro-fuzzy systems and statistical modeling techniques from parametric and non-parametric analyses. Kaplan-Meier survival analysis model was the non-parametric method used. To identify risk factor, back-propagation algorithm was used. Outputs of the ANN were lifetime of segments and observation result (breakage or no-breakage). The outputs were used for pattern recognition and to rank relevant weights of risk factors. Kernel smoothing was employed for regression and Kaplan-Meier models by utilizing a joint probability density function. The models were verified using historical database of New York City. Results proved previous findings that pipe material, diameter and breakage history have highest effects on pipes. Risk factors were found and ranked using pattern recognition and incomplete datasets. The model is site-specific and is developed only for the assumed situation. Parameters used for this model were pipe material, diameter, length, breakage history, traffic, and intersection block.

Al-Barqawi and Zayed (2006) presented a condition rating model for underground water mains to evaluate the maintenance priority using back-propagation algorithm in ANN. The condition rating was between 0 meaning poor to 10 representing excellent condition. Model was verified through 3 case studies and results showed that model can predict pipe condition favorably. Within this model, it is believed that breakage rate and age have the most influence on pipe condition. Data requirements for this model were soil type, road surface, pipe cover, diameter, material, age, number of breaks and the Hazen-Williams C-Factor.

Achim et al. (2007) proposed a model for prediction of failure in water pipe asset using neural networks. The ANN model in this paper comprised an input layer with six nodes, two hidden layer with sixteen nodes both and an output layer with one node. Bootstrapping and random sampling were used for validation of the model. The model proved to be an acceptable solution for complex problems with less calculation. The input parameters are pipe diameter, age, length, year of construction and location. Future evaluation for this model considers climate factors and corrosion.

Geem et al. (2007) presented a trenchless water pipe condition assessment using artificial neural network and multi-layer perceptron model (MLP). The model used back-propagation algorithm and the pipe condition was evaluated using five factors of outer corrosion, crack, pinhole, inner corrosion and the Hazen-Williams C-factor. Comparing the predicted data by model and observed data analyzed by multiple linear regression (MLR), ANN produced a higher determination and considered nonlinearity in input data. The input variables for this model were pipe material, age, diameter, pressure head, inner and outer coating, electric recharge, soil and bedding condition, trench depth, and the number of road lanes used.

Amaitik and Amaitik (2008) developed a PCCP wire breaks prediction model using artificial neural networks. This could help the authorities to monitor, inspect and repair the water distribution network. The model was verified by comparing the results to MLR model. Analysis showed that ANN model predicts wire breaks more competent than MLR model. A break pattern was also found in predictions. The model entailed use of 9 independent variables of monitoring period, pipe age, soil resistivity, design pressure, soil density, soil cover, type of pre-stressing wire wrap, wire diameter and wire pitch.

To summarize, ANN models are able to cover non-linear and complex behavior of water networks. They also cover numerous variables which increase system performance reliability. One limitation for this methodology is that there is no description about the creation of the black box. Furthermore, ANN models are not able to predict future failure rates for other areas.

2.4.4. Heuristic models

This methodology is used for those problems that have limited data. It captures expert opinions about importance of effective parameters on a specific issue. Some of the researches about use of heuristic models are presented here.

Kleiner and Rajani (1999) proposed a multi-step process to assess future needs in water pipelines using limited data. The multi-step process consists of: 1. collecting data where data for prediction of future breaks is scarce, 2. classifying data into different groups, 3. determination of service life utilizing breakage rate, 4. inspecting different scenarios of expected life, 5. calculating the replacement cost of water mains. Since there is limited data, a heuristic model is necessary to employ three probability distributions of Weibull, Gumbel and Hertz. The model was verified through a case study and results showed that during the first 30 years, all distribution predicted same replacement age. Analysis also revealed that pipe age, soil type and operating pressure are the most critical factors in breakage rate. Data used for this assessment is vintage, soil type, diameter, region, length, operating pressure, road type, surface condition, foundation state, and traffic loading.

Watson et al. (2004) proposed a Bayesian-based pipe failure model to predict failure rate. This hierarchical model collects data from different data sources such as engineering knowledge and historical failure data. The model considers hyperprior distribution for failure rates. This distribution determines the influence of individual failure on other pipes in network. In process of validation, the model was validated with two pipes and the break rates were illustrated versus time in predicted models and observed data. Until pipe reaches age of 25, Bayesian model predicts better results than normal estimation. After that, the results from both the models are similar.

Al-Barqawi and Zayed (2008) presented a model using analytic hierarchy process (AHP) for water main conditions assessment. AHP quantifies qualitative engineering knowledge of experts about important factors in pipe failure. In this model, the effective factors were first recognized; then pair-wise comparisons were performed between each two of the factors and priorities were assigned. Afterward consistency analysis was performed and condition assessment records were calculated from priority matrices. The condition assessment values ranges from 0 (critical) to 10 (excellent). Factors considered in this study are soil type, groundwater table level, pipe diameter, material, age, breakage rate, Hazen-Williams C-Factor, Cathodic protection, type of traffic/road, type of service, and operational pressure.

Al-Barqawi and Zayed (2008) also did another research about an integrated AHP/ANN model to evaluate municipal water mains' performance. They first utilized AHP to calculate the weights and assign a value between 0 (critical) to 10 (excellent) to the condition of pipeline. After that, ANN model was employed to solve the problem of missing data using pattern recognition. The model was validated through data from three case studies. Results show good correlation between observed and predicted data. Parameters considered in this study are pipe material, diameter, age, soil type, groundwater table level, average daily traffic, type of road and service, number of breaks, Hazen-William coefficient, Cathodic protection, and operational pressure.

Zhou et al. (2009) developed a Fuzzy based pipe condition assessment model using PROMETHEE. PROMETHEE is a method of outranking which establishes and uses relationships between indicators in order to weight pipes. The model generates pipe condition rating using AHP from fuzzy first-level and second-level condition indicators. The model was validated using eight pipe samples. The parameters used for first level condition indicators are physical indicators, load, external corrosion and historical breakage. Pipe diameter, age, length, depth, water pressure, impact strength and maximum pressure are the data requirements for second level condition indicators.

As can be seen, the heuristic models entail inconsistency in expert judgments. Since the experience differs from individual to individual, the judgments are different. However, the heuristics models are simple and could be utilized as an initial phase for evaluation of failure rates.

2.4.5. Fuzzy logic models

Fuzzy logic is employed to deal with systems with inexact information and uncertainties. Numerous applications of this methodology have been reported in infrastructure management including 10 articles about water distribution networks.

Kleiner et al. (2005) proposed a fuzzy Markov deterioration process to model failure risk of PCCP, cast and ductile iron water mains. Triangular memberships and fuzzy rules of "if-then" were employed to solve the problem. Condition of the asset was calculated from the present condition and deterioration rate, which had been identified from Markov deterioration process. The data requirements of the models were pipe age, pipe material, external pipe barrel/bell, inner lining, pre-stressed wire, concrete core, pipe geometry and joint. This model has not been validated due to lack of data.

Rogers and Butler (2005) developed a neuro-fuzzy spatial decision support system for pipe replacement prioritization. The model includes fuzzy logic and neural network back propagation algorithm which relates certain characteristics to pipe replacement. Input-output pairs of burst records together with pipe characteristics were used to train the model. Since data needed pre-processing, Bayesian statistics model was employed. Results showed that training improves model performance. The input parameters for the model are soil type, pipe density, age, diameter, material, street type and maximum pressure.

Najjaran et al. (2006) presented a fuzzy expert system to assess corrosion of cast/ductile iron pipes from backfill properties. The model comprises subjective and objective parts and two systems were suggested for fusion of the subjective and objective models. The first system determines deterioration rate using soil properties and the second determines corrosivity potential from soil samples. In the process of validation, a series of soil samples were utilized. The extracted variables from the soil samples were soil resistivity, soil pH, percentage of clay fines, soil redox potential and sulfide, pipe age and maximum pit depth. This methodology was also used in two other articles of "A Fuzzy Expert System for Deterioration Modeling of Buried Metallic Pipes" (Najjaran et al., 2004) and "Fuzzy-Based method to evaluate soil corrosivity for prediction of water main deterioration" (Sadiq et al., 2004).

Rajani and Tesfamariam (2007) proposed an approach for estimating time to failure of cast-iron water mains. The fuzzy membership function employed in this model is triangular fuzzy numbers. Π and N are two measures for uncertainty, Π accounts for possibility while N accounts for necessity. Failure occurrence which is stated by means of factor of safety should be between Π and N. Model presented by Rajani and Tesfamariam (2007) is identical to one presented in "Estimating Time to Failure of Ageing Cast Iron Water Mains under Uncertainties" (Rajani and Tesfamariam, 2005) and "Possibilistic Approach for Consideration of Uncertainties to Estimate Structural Capacity of Aging Cast Iron Water Mains" (Tesfamariam et al., 2006). A case study was used to validate the model. Results showed large and small diameter pipelines are more susceptible to external loads and bedding loss respectively. Input parameters required for this model are elastic modulus, normal and bursting tensile strength, ring modulus of rupture, Poisson's ratio and fracture toughness, pipe nominal diameter, thickness, length, thermal coefficient, soil unit weight, trench depth and width, unsupported length, soil dead load and traffic live load, water pressure, transient water pressure, remaining wall thickness and temperature difference.

Fares and Zayed (2010) presented a hierarchical fuzzy expert system for risk of failure in water mains. The 16 input parameters are classified into 4 groups of physical, environmental, operational and post failure. The risk of failure varies between 0 (least risk) and 10 (highest risk). At first, the impact factor of the parameters of four categories were evaluated utilizing the Mamadani rule system. Then, they were used to calculate the risk of failure. The model was verified by a case study that resulted in the fact that cast iron and small size pipes are the most sensitive parts in the network. The input parameters are type of soil, average daily traffic, groundwater level, pipe diameter, material, age, protection method, breakage rate, hydraulic factor, water quality, leakage rate, cost of repair, damage to surrounding, loss of production, traffic disruption, and type of serviced area.

This kind of performance models are mostly used where there is lack of data and the relationship between parameters are vague. One challenge in this methodology is choosing the fuzzy rule sets and defining the defuzzification procedure. Choosing triangular fuzzy numbers are more common in literature.

2.4.6. Summary

The deterioration models can be grouped into five categories of deterministic, statistical and probabilistic, artificial neural network (ANN), and heuristic models based on the methodologies employed. Each method has its own features. Deterministic and statistical models entails use of sample specimens and large number of long term observed data while fuzzy and probabilistic models are often used when data is scarce or there is very limited information. Most of the methodologies such as deterministic, probabilistic and ANN are site-specific and it is not possible to generalize the results unless the situation remains the same.

The relationships between the parameters are certain in deterministic models whereas fuzzy models are utilized in the situations where cause-effect knowledge is imprecise. Moreover, as ANN seems like a black box, there is no description about the creation of neural network. As can be seen from models, ANN, heuristic and fuzzy models are recently developed and proved to be more efficient than previous models, e.g. ANN and fuzzy models consider more parameters than others. Future works are required to propose generalized models, which considers further parameters and utilizes less data requirements.

2.5. Maintenance scheduling models

Renewal and replacement scheduling models are mostly used optimization methods to develop a cost-effective and appropriate model for rehabilitation programs. Nowadays, application of Genetic Algorithm as a method of optimization is very prevalent in literature and there are several studies about optimized maintenance scheduling for different assets. It is merely because of the robust search abilities of Genetic Algorithm which can undertake complexity of outsized optimization problems. Those with focus on water distribution network will be explained here. Kleiner et al. (1998) proposed a methodology in which structural and hydraulic deteriorations are considered to analyze economic and hydraulic capacities of pipe segments in water distribution network over a planning horizon. The model in this study carried out this methodology into a decision support system which chooses rehabilitation alternative for each pipe segment of the network to minimize the cost of maintenance plans. The validation process entails comparing results to the data gathered from a restricted exhaustive enumeration and by asking questions from experts and managers. Bach et al (2000) suggested new approaches for optimal repair fund assignment and allocation of budget in water distribution networks. The model assumed there is no limitation for the budget at first and developed to allocate the funds and then it optimized the allocation of the limited budget for the city. The ultimate goal of model is to minimize the total cost of repair and water loss. The actual data of the network of Ho Chi Minh City in Vietnam is used as the numerical example in this study to display the practicality of the proposed models. Mailhot et al. (2003) defined an optimal replacement standard for individual pipe based on their expected future costs estimated form conditional probability function. To minimize the cost, hazard functions are involved to estimate a critical pipe break order in order to perform replacement.

Moglia et al (2006) have developed PARMSPRIORITY method to support decision making in replacement scheduling of water pipelines. Previously, similar method of PARMS-PLANNING provided decision makers with long-term plans and budget set-ups associated to pipe replacement. This model performs risk calculation from asset and failure records data and then predicts the failures. After that, it estimates the related costs and evaluates the scenarios. Based on the application of PARMS-PRIORITY in two water utilities, it has the potential to be a useful tool for rehabilitation scheduling. Alvisi and Franchini (2006) recommended a multi-objective rehabilitation scheduling which aim to minimize the total cost associated to repair or renewal of pipelines and maximize hydraulic capacity of the network. The budget is constrained over a selected period. In addition to the optimizer, there is a hydraulic simulator which identifies hydraulic and breakage situations. Applying the proposed model to a case study showed that the methodology is beneficial for future rehabilitation scheduling. The authors later developed a procedure for multi-objective optimal medium-term scheduling in rehabilitation and leakage detection of water distribution systems. They assumed a predetermined budget constraints and identified the time and location of the pipe segment that should be replaced. The objective of this study are to minimize the volume of the wasted water through breakage and leakage and repair costs of the breaks. The outcome of this research is not only one optimal solution but also the Pareto front of other solutions. This model has applied to a real case study and results showed that the proposed methodology is appropriate for leakage detection and rehabilitation strategies (Alvisi and Franchini, 2006). Nafi and Kleiner (2009) proposed an efficient scheduling renewal method for water pipes focusing on individual water mains. They considered adjacent known infrastructure works and economies of scale and built their model based on short to medium planning period. The projected solution of the model is different combinations of segment renewal programs for decision makers.

2.6. Related research techniques

2.6.1. Delphi technique

Delphi technique was first introduced in 1950s in RAND Corporation. It is a decision making method based on opinions of experts (commonly referred to as the panelists, participants or respondents) concentrating on a certain issue. It is supposed that several people are more unlikely to make wrong decision rather than an individual over an issue (Hasson et al., 2000). Delphi is also defined as "allowing a group of individuals, as a whole, to deal with a complex problem while avoiding their direct confrontation and retaining their interactions" (Linstone & Turoff, 1975).

Anonymity, iteration and controlled feedbacks from prior round to the current round, statistical aggregation of group responses and expert panels are the key features of the Delphi. Anonymity is achieved by performing the survey through emails or personal interviews because when the respondent put his/her name on an idea, it would be more difficult to change the idea later (Ngeru, 2012). Iteration and controlled feedback provide refined results. Statistical aggregation is completed through quantitative analysis and data interpretation (Ngeru, 2012). This technique is considered as quick, not costly and relatively competent way to obtain consensus from opinions of the panelists (Von Der Gracht & Heiko A, 2012) and has the potential to investigate the issues that necessitate judgment. On the contrary, some researchers believe that it is very time consuming and labor intensive (Gary & Heiko, 2015). Delphi has also been criticized for forcing panelists to reach a consensus and having no area for the participant to clarify their opinions (Hasson et al., 2000).

In the process of the Delphi, the problem statement should be defined at first. Then a panel of experts familiar with the subject is selected. Since Delphi is a group decision technique, it needs several experienced experts familiar with the issue who could deliver correct answers to the questions. Therefore, the process of selecting skilled panelist is of major importance (Okoli & Pawlowski, 2004). Most of the studies use 15 to 35 experts as a panel; however, there are evidences of participation of 100 to 1000 respondents in the literature. Reid reported panel sizes of 10 to 1685 from the previous studies (Reid, 1988). Murphy noticed that there is no empirical relationship between number of experts and validity and reliability of the survey and some researchers believed that number of experts is subjected to the available resources and scope of the problem. Murphy also suggested that the geographical diversity of the members leads to consideration of exhaustive aspects of the issue and results in better decisions (Meijering, Kampen, & Tobi, 2013). Afterwards, the first questionnaire is designed which provides information on the issues it has been designed for. The questionnaire must be sharp and answerable. Usually, the questions are designed by a small group of experts, however there are few cases in which a semi-structured questionnaire or structured questionnaire were used to collect data in the literature (Powell, 2003).

Giving feedback to the participants helps them to figure out whether they may have failed to consider any parameter and gives the panelists the opportunity to revise their answers if necessary (Mutikanga, Sharma, & Vairavamoorthy, 2011). The survey continues until the expected convergence achieved or the law of diminishing returns sets in (the number of returns decreases). It should be noted that early finishing of the survey causes erroneous results and many rounds would waste expert's time. Three to four rounds are reported in most of the literature (Xia, 2010). However, several studies showed that two or three rounds are ideal. It is believed although two or three rounds gives the approximate convergence in the collected responses, more rounds would not result in increased accuracy of the decision. Moreover, balance of time, cost and possible participant's fatigue should be considered (Powell, 2003; Yu et al., 2014).

One limitation in Delphi technique is level of response which needs to be high in reaching a consensus (Yeung, 2007). The panel of the experts should include both academic and technical individuals to prevent from biased conclusions based on their background (Mack, 2011). The success of the Delphi highly depends on the skills of the researcher. He has to track the respondents from the first round to the end, reminding them to fill the questionnaires and analyzing the collected responses (Hasson et al., 2000).

2.6.2. Analytical Hierarchy Process (AHP)

AHP gives weights to set of variables by organizing experience and judgments of individuals into hierarchical structure. This structure illustrates relationships between goal, parameters and sub-parameters. Fuzzy analytical hierarchy process (FAHP) is the fuzzy format of AHP and is a well-known multi criteria decision making technique introduced by Saaty in 1988. It could be said that the ultimate goal of the AHP is collecting the expert's judgment, however it is not able to reflect the uncertainty in the judgments and knowledge of humans in decision making process precisely. The uncertainty could be modeled using fuzzy logic. It adds two more inputs and respectively two other outcomes of smallest and largest possible values. FAHP is used to solve the hierarchical and multi criteria decision making problems by using trapezoidal and triangular fuzzy numbers. These two mentioned fuzzy numbers are mostly used to reduce the complexity of the problem due to the large number of criteria and decision makers. The fuzzy characteristics should be compared and ranked to find the priority of the criteria.

When the judgments are made, the hierarchical levels are ready to be analyzed using FAHP. The experts are asked to identify the relative importance of each criterion separately and respect to other factors in AHP. AHP has some limitations such as subjectivity and it does not consider uncertainty in inputs. FAHP has solved this problem; however, it is time-consuming if calculations are done manually. In FAHP, the experts are asked to enter all possible outcomes of modal, lowest and highest possible values in the pairwise comparison matrix. It means that they are entering the values three times more than they enter in regular AHP which is difficult and time consuming (Fares, 2008). To analyze FAHP, Laarhoven and Pedrycz (1983) suggested a method which was based on minimum logarithmic squares. This method did not become popular due to its complexity and ambiguity (Nepal et al., 2010). After that, Chang (1996) proposed a method called 'the Extent Analysis Method (EA)' which uses fuzzy triangular numbers and becomes more common in FAHP calculations (Nepal et al., 2010). In this study, the EA method is chosen for analysis and more details will be described in the next Chapter.

2.6.3. Shannon Entropy

In 1984, Claude Shannon proposed a mathematical theory to measure amount of information content of an information source. The concept of this theory has been used in a variety of scientific areas such as physics, social science, and etc. It was taken from definition of entropy by Boltzmann in the second law of thermodynamic, which describes entropy in terms of uncertainty in energy states of a system. In this mathematical theory, the term of Entropy, refers to the portion of information content. This portion indicates the uncertainty of both the information source and the random variable and defines how much information is earned when result i is observed. When the raw data of the decision making matrix are identified completely, Entropy method could be used to evaluate the weights. There is more chance of occurrence for each value of i when entropy is higher. Considering P as a random variable and p_i as the probability, the theory identifies the relationship between Shannon's Entropy E and random variable of all the n criteria (Shannon, 2001):

$$E_i = S(P_1, P_2, \dots, P_n) = -E_0 \sum_{i=1}^{n} P_i \ln(P_i) \qquad 2.3$$

Where n is the total number of possible outcomes. Measuring uncertainty of a random variable i means that when $E_i = 0$, i would be a certain variable not a random one. Also in case of maximum quantity of E_i, i is a random variable with uniform distribution. In this formula, entropy and uncertainty are used for the same concept. In other words, average quantity of information which is collected after the observation of result x_i in the random variable of X, is entropy. Lotfi and Fallahnejad (2010) classified Shannon Entropy into Interval Shannon's Entropy and Fuzzy Shannon's Entropy and proposed a method to solve them.

2.6.4. Fuzzy Logic

Fuzzy set theory was first proposed by Zadeh in 1965. The theory is based on the fact that "goals, criteria, consequences of a decision making process in real world are ambiguous" (Ozer, 2007). Therefore, decision makers prefer to express their opinions in a range instead of an exact value. Fuzzy theory covers four main concepts: fuzzy sets, linguistic variables, possibility distributions and fuzzy if-then rules. A fuzzy set A in X is defined by a membership function $f_A(x)$ which associate a real number in the interval [0, 1] to each point of X. The value of $f_A(x)$ represents the grade of membership function. If $f_A(x) = 1$, it means that x is fully belongs to A and x does not belong to A, if $f_A(x) = 0$ (Zadeh, 1965). Approximate environment is well illustrated by fuzzy logic and it can be utilized in mathematical operation. Thus, the use of fuzzy logic has a sudden growth during the past decades.

Fuzzy membership functions are those functions that relate outputs to inputs. There are many forms of membership functions, however, main ones are triangle, trapezoid, bell curve, Gaussian and sigmoid. Trapezoidal membership function is identified by four parameters while Gaussian and sigmoid membership functions are represented by two parameters. Bell shaped functions are identified by three parameters of width, slope and center of the function. Triangular function only has three possible outcomes of smallest possible, most probable, and largest possible value of the phenomenon. Triangular membership functions are the most popular function in literature and are the most common functions in fuzzy applications.

2.6.5. Artificial Neural Networks

Artificial Neural Network (ANN) technology is a predictive artificial intelligence that can model the comprehensive and complex real systems and recently has substituted regression analysis (Baxter et al., 2002). Since ANN is very fault tolerant and generalized, it encompasses uncertainty which makes it an appropriate solution for infrastructure management problems (Baxter et al., 2002). It is designed based on the learning mechanism of human brain. Due to the ability of ANN to learn by example, Sawhney and Mund (2002) believed that ANN is very effective and significant in data related problems. ANN is composed of neurons and layers. Neurons are classified in layers and are working together. The layers generally are the combination of an input layer, hidden layer(s) and an output layer. The input layer includes the input data which the analysis is based on whereas the output layer illustrates the product of the model. The number of hidden layers is defined by trial and error and may rise in relation to the complexity of the problem (Fahmy & Moselhi, 2009; Khan et al., 2010). There are lots of learning methods in ANN, however back-propagation approach attracted the most attentions in construction management studies.

Sbarufatti et al. (2005) reported that ANN has two phases of learning (training) and recalling (testing and validation). Learning phase finds the relationship between parameters and recalling predicts output from the input based on the trained network. In unsupervised learning the output is unavailable in the training phase, otherwise it is supervised. In the training phase, the network trains itself through data records to figure out a relationship between inputs and outputs by adjusting the weights. The purpose of training is that certain input results in a particular target value and adjustments are made to network based on the differences between target values and outputs until they match. If learning process is finished faster, then the network performance will improve. Thus, the network inspects the pattern in order to stop training when error is about to rise.

In ANN, both weight (w) and bias (b) are scalar parameters of the neurons which can be modified. Bias is similar to weight excluding that it has a fixed input of 1. These two parameters are adjusted until the network models the behavior successfully (Achim et al., 2007). Neurons of each layer are connected to others through connection lines which has an assigned weight. These weights are summed with bias ultimately to construct the “NET neuron”. To evaluate the accuracy of the model, Mean Square Error (MSE) is applied which calculates the sum of differences between output and target values (Nazari et al., 2015)

The ANN has its own advantages and drawbacks. The key benefit is the ability to load historical data in order to train and modify the neurons weights until output values reach target ones. As for the limitation of the ANN, it is believed that the training speed is slow, the structure is not precise and the optimum design is not very wisely directed. Furthermore, the black box nature of the ANN prevents from understanding the weights of network.

General Regression Neural Network (GRNN) is often used for nonlinear function approximation. It has a special linear layer and a radial basis layer which makes it different from radial basis network. It was first proposed by Donald F. Specht in 1990. GRNN falls into the class of probabilistic neural networks and requires less training samples in comparison to a backpropagation neural network. Since available data from training the networks are not usually sufficient, probabilistic neural networks are of interest. Therefore, GRNN is a very beneficial tool for approximation of smooth functions. It is able to solve any function approximation problems in case sufficient data is available in short time. The only limitation of GRNN is dimensionality since it is not able to ignore unrelated inputs itself and needs major modifications in algorithm. Consequently, this method is not chosen in problems with more than 5 to 6 related inputs.

2.6.6. Genetic Algorithm

Genetic Algorithms were first introduced by John Holland in 1975. They are stochastic and random algorithms which imitate the natural selection and are based on genetics. GA generates optimal solutions through developing new and improved generations from parents holding best characteristics repetitively. The whole process is started through producing the first population in which members are selected randomly or based on some rules. The fitness function is defined and calculated for each chromosome. Since fitness function values show how much optimal each solution is, the best individuals are chosen for mating pool. Next generation is produced through crossover in which two parents who were selected from the pool, exchange their genes and create offspring. The main limitation of crossover is that it reduces the variety of the population. That's why mutation is needed. Mutation is employed in offspring pool and altered portion of offspring's genetic. The chromosomes of the new offspring are compared based on fitness value to select the best chromosomes for the next generation. These steps are repeated until no further improvement is recognized and the best solution is identified.

Haupt et al. (2004) summarized the GA implementation steps into 7 steps:

1. Initialize the first population: the first population namely parents are generated which are set of solutions (chromosomes). This population size should be large enough to accomplish the favorite solution. However, a satisfactory size could assure the least elapsed time for running the algorithm.
2. Determine the fitness function: fitness function is the objective function which solutions will be evaluated based on.
3. If the results are satisfactory, then select the best solution
4. Else, choose new parents.
5. Crossover: crossover means the mixing of chromosomes of parents to initiate a new generation and mostly generates better solutions. The most common crossover methods are single point crossover, two-point crossover and uniform crossover.
6. Mutation: considering new and undiscovered genes in the population is mutation
7. Go to step 2: This step is used to prevent from choosing non-optimum solutions.

Single objective optimization has only one optimal solution, while multi-objective optimization has more than one objective that should be achieved. Therefore, there are more than one solution which can be considered as near-optimal solutions. Consequently, ranking tools such as Pareto Front, TOPSIS, EZStrobe, etc. should be employed to help in deciding which near-optimal solutions is the ultimate optimal solution.

GA has major advantages in comparison to other methods. It can run the optimization with both discrete and continuous variables and is able to deliver not only one solution but a list of solutions. Moreover, GA can solve different objective function and can deal with complicated cost problems.

2.7. Findings, Limitations, and Research Gap

There has been extensive endeavor to address different aspects of water distribution networks such as the inspection methods, deterioration, residual life and rehabilitation plans of the pipelines. In the case of inspection, literature review proved that since each method has its own features, a hybrid two-tier method is needed to employs more than one technology, for timely assessment and cost reduction. Some researchers have tried to develop performance models for each aspect; however, literature review confirms that the existing research works have not developed a comprehensive model that predicts condition and residual life of the pipes and construct the rehabilitation plans based on the constrained budget. Most of the previous studies concentrated on one aspect of the pipelines such as deterioration curves, failure rate or condition. Considering the existing deterioration models, it could be seen that each model considers different variables to predict deterioration and remaining useful life in pipeline. It is assumed that certain variables have been selected in these researches because they are available rather than important. Therefore, a part of this study deals with prioritizing the factors affecting the deterioration and residual life based on their significances. Two methods were used simultaneously to consider both subjective and objective weights of the parameters. Furthermore, most of the models are site-specific and are applicable only for those particular situations they have been designed for. Therefore, a comprehensive model is needed to cover the limitations of the previous models and predict the performance of the pipes regarding their different features.

Mostly in pipe repair programs of faulty water distribution network, whenever a leak is detected, the pipe goes under maintenance. This will repeat until allocated funds are terminated. The budget is generally billed on yearly basis without careful analysis. Therefore, an optimized replacement and rehabilitation strategy is needed to prevent budget from exhaustion. In the literature review, several powerful methods were found that can be used for efficient scheduling the replacement and renewal of water pipeline. For example, it was found that Genetic Algorithm is a strong method for prioritizing the pipelines for replacement or rehabilitation in small networks when there are multiple objectives to satisfy. However, this method would be more powerful when it is combined with another analytical method such as neural network. Since neural network is able to cover non-linearity and complexity of water network behavior and it is capable to deal with numerous variable, it would boost the prediction capability of the model by being used in predicting the remaining useful life of the pipeline. Also the maintenance plans would be more cost-effective when rehabilitation and replacement strategies are selected considering a constrained budget and the estimated remaining useful life along with the predicted breakage rate.

CHAPTER 3: RESEARCH METHODOLOGY

3.1. Chapter Overview

This chapter starts with a section which elaborates the overall research methodology of this thesis. It goes briefly on the developed models and schematically displays the steps of the calculations at first (section 3.2). Next, the condition model is addressed and its three consecutive phases are discussed to show how condition index is calculated (section 3.3). Section 3.4 is about the way neural network is applied to calculate the remaining useful life of the water segments in a network and several models are trained to find the most accurate model for RUL prediction. This chapter is wrapped up by budget allocation model (section 3.5) which explains an optimized budget allocation model for water distribution network. The constrained budget is assigned based on the remaining useful life and breakage rate of each segment in the design horizon and the model define the replacement and rehabilitation programs of the network for different horizons.

3.2. Overall research methodology

The overall flow of the research process is depicted in Figure 3-1. As Shown, the research starts with comprehensive literature review about factors influencing the deterioration and leak detection methods. Existing deterioration models and decision making techniques were also studied to make use of them in the analysis. Preliminary analysis is commenced by distributing and collecting the first series of questionnaires about factors affecting deterioration for three rounds. The questionnaires are analyzed and the parameters of the model are selected through Delphi survey.

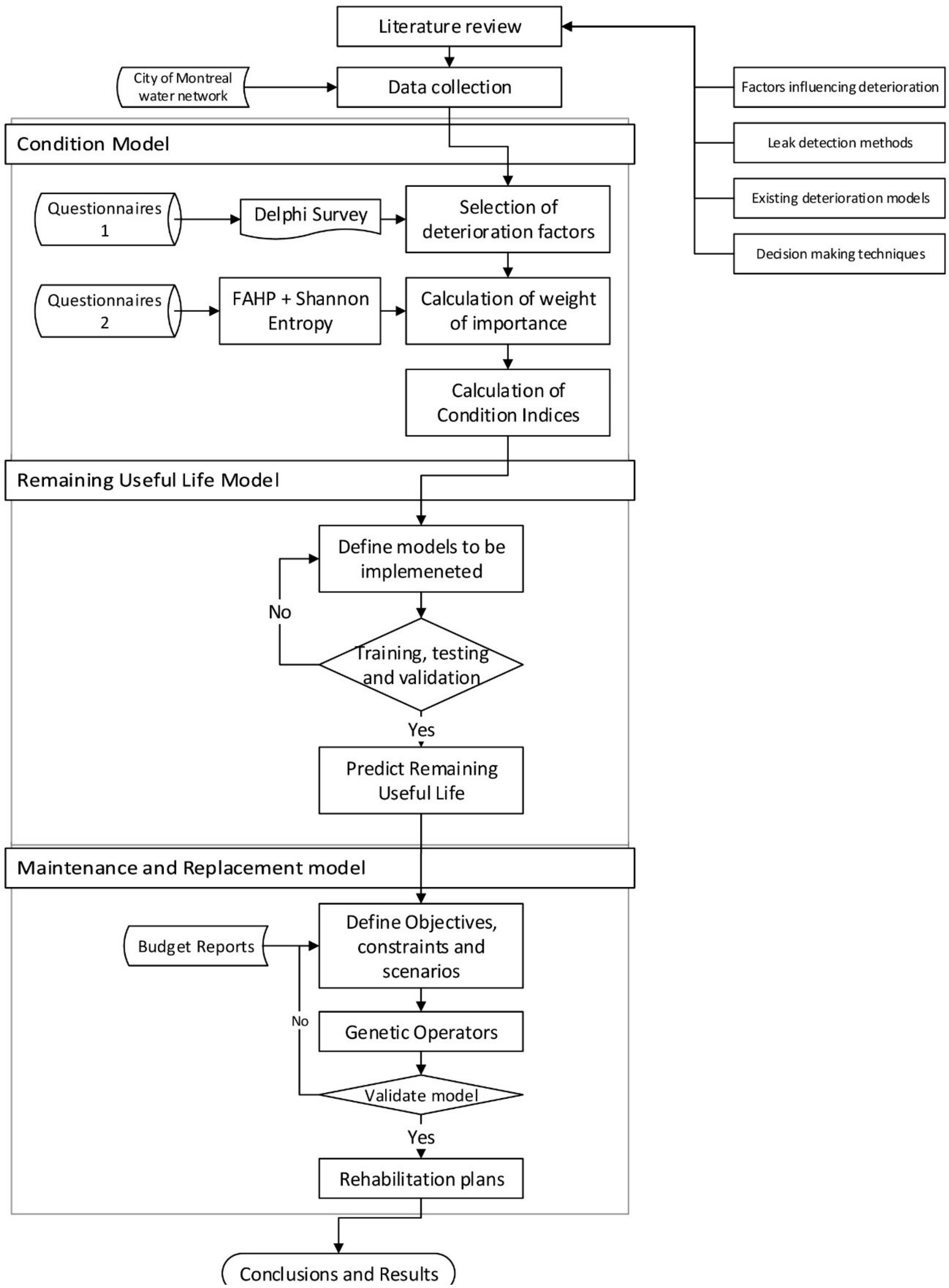


Figure 3-1. Main flowchart of the thesis

3.3. Condition model

3.3.1. Identification of contributing deterioration variables

The flowchart diagram of this part is illustrated in Figure 3-2. The study was conducted to find the important parameters in deterioration. Delphi is used to collect data since it is capable to explore answers for designed questions as addressed in section 2.6.1. First, the problem should be defined and all the aspects of the issue should be considered. After that, the questionnaire is designed and the experts were selected considering their expertise in water and pipeline. The success of Delphi obviously depends on the related expertise of the panelists. The required expertise was divided into three categories: piping, water and maintenance. To select the experts, their personal social networks were reviewed and the name of those who would fit into categories were written. Since the personal contacts of the researcher are limited and biased, different municipalities were contacted and asked for experts who have deep understanding in mentioned categories.

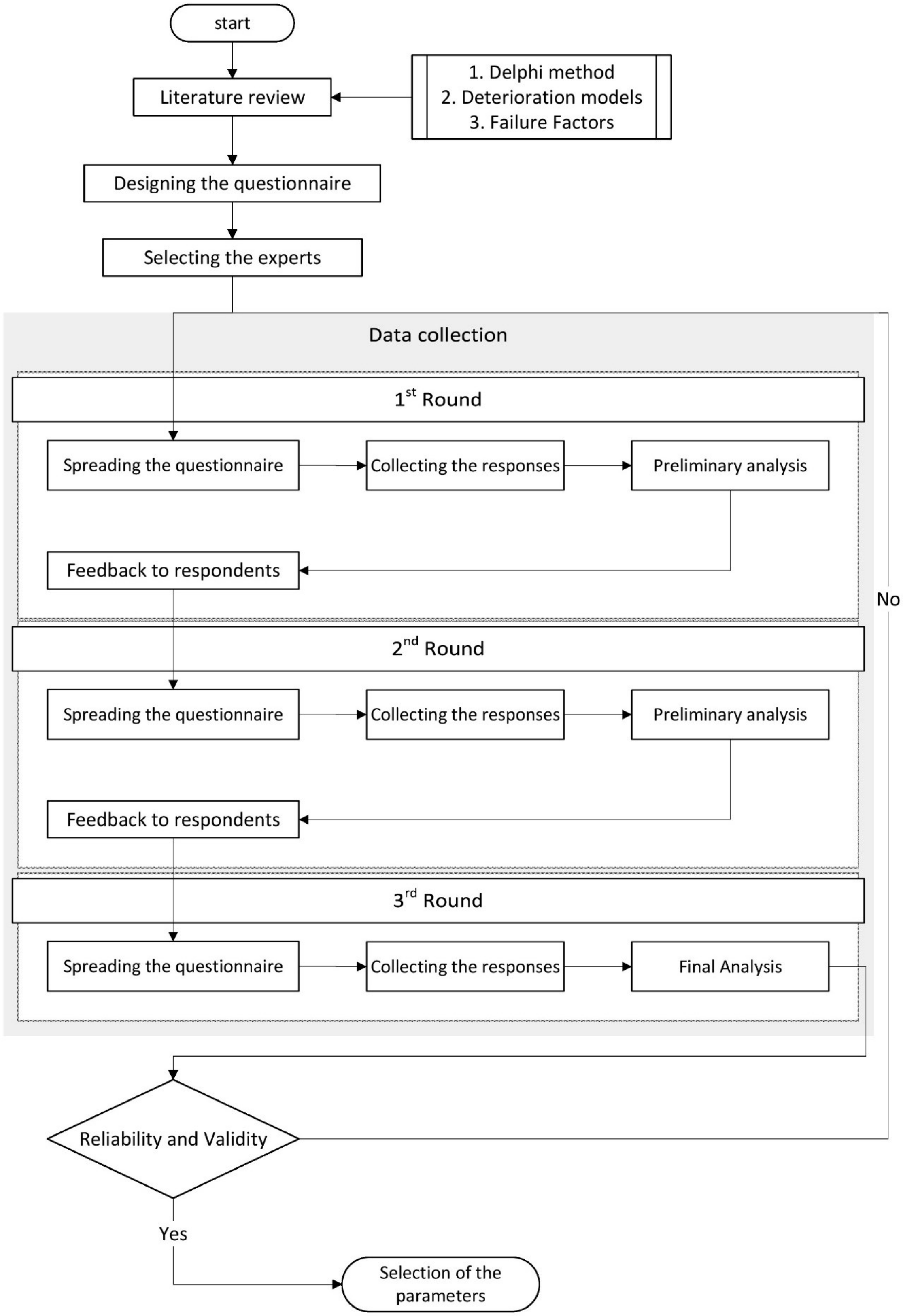


Figure 3-2. Flowchart of Delphi method

Afterward, the experts received “qualification checklist” and declared their expertise. Those experts that have not enough knowledge were politely excused. Once the list of panelists is prepared, they are contacted individually. The initial questionnaire would be delivered to the panelists when they approve to participate in the survey. Most of the experts believed that the listed factors in the questionnaire are sufficient; therefore, the questionnaire would not go under any changes during the survey.

In this study, Data collection was performed through 3 rounds of survey. In first round 46 online questionnaires were sent to the panelists via e-mail, 46 responses were received and analyzed. From those who completed the first round, 13 experts responded to the second round modifying their judgments while 21 panelists responded without any revision to their answers. In the third round, none of the respondent desires to revise his answers and Delphi survey was terminated. This study was performed anonymously in all the three rounds and final results were delivered to the panel. The responses to the questionnaires were analyzed to check the reliability and validity of the results. Since Delphi doesn’t need the experts to meet physically, therefore survey could benefit from the international judgments as well.

After collecting questionnaires from experts, their validity and reliability should be checked. It is important to know the connection between the validity and reliability. Reliability is necessary for validity but it is not satisfactory alone (Litwin, 1995). Validity which means accuracy in question design is measured in four forms: face, content, criterion and construct validity. They could show whether the questionnaire is able to measure the specific characteristic that it has been designed for or not (Litwin, 1995). Litwin reported that face validity is not an acceptable measure of validity at all. He also believed that content validity is very qualitative (Litwin, 1995). Construct validity which relies on a clear explanation of the construct, is the most valuable and difficult one (Okoli & Pawlowski, 2004). Delphi method can contribute to construct validity since it uses successive rounds of the questionnaire and researchers could make sure that the respondents understand the items correctly (Hasson et al., 2000). Also the parameters' description part in the questionnaire moves towards understanding the construct by respondents. The construct validity could also be checked by asking the experts to validate the final results. This validation step is permitted since the respondents are not anonymous to the researcher (Okoli & Pawlowski, 2004).

Reliability refers to the fact that whether the questionnaire produces the same output under the same conditions (Litwin, 1995). In other words, it refers to consistency of the results. Similar to the case of validity, reliability could be assessed in three aspects: test-retest, alternate–form and internal consistency reliability (Okoli & Pawlowski, 2004). They believed that test-retest reliability is not relevant to Delphi as it is expected that respondents revise their responses each round (Okoli & Pawlowski, 2004). The internal consistency is checked for the first and second rounds of questionnaire by calculating the Cronbach's coefficient Alpha for respondents through SPSS. It is calculated as shown in following equation in which σ_X^2, σ_Y^2 and K are variance of the total scores, variance of the components and number of components respectively. If Cronbach's Alpha becomes greater or equal to 0.9, the internal consistency is Excellent (Litwin, 1995).

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{K} \sigma_Y^2}{\sigma_X^2}\right)$$

3.3.2. Estimation of the relative weights

In this section, another questionnaire was designed to find the weight of importance of factors and was distributed among experts at first. Then the weights of importance of factors affecting the deterioration are defined through FAHP. Afterwards, Entropy method is applied to find the relative weights and finally an integration of Shannon Entropy and FAHP is utilized to calculate the weights. Figure 3-3 shows the process for finding weights of importance for parameters. Different parts of the flowchart are described in the following sections. These methods are chosen based on the advantages stated in section 2.6.2 and 2.6.3 respect to other methods.

The very early step for analysis is building the matrix for pairwise comparison based on the collected responses from experts and checking its consistency. After that, the relative weights of parameters and sub-parameters were determined (Vahidnia et al., 2008).

$$A = \begin{vmatrix} 1 & W_{12} & \dots & W_{1n} \\ W_{21} & 1 & \dots & W_{2n} \\ \vdots & \vdots & 1 & \vdots \\ W_{n1} & W_{n2} & \dots & 1 \end{vmatrix}$$

In this matrix, w_{12} is the weight of parameter 1 respect to parameter 2. All the arrays in matrix A are fuzzy triangular numbers of (l_{ij}, m_{ij}, u_{ij}) and the weight vector is defined as:

$$\mu_{ij}(W_{ij}{}^{*}) = \begin{cases} \dfrac{m_{ij} - (W_{ij})}{m_{ij} - l_{ij}} & 0 < W_{ij} < m_{ij} \\ \dfrac{(W_{ij}) - m_{ij}}{u_{ij} - m_{ij}} & W_{ij} > m_{ij} \end{cases} \qquad 3.1$$

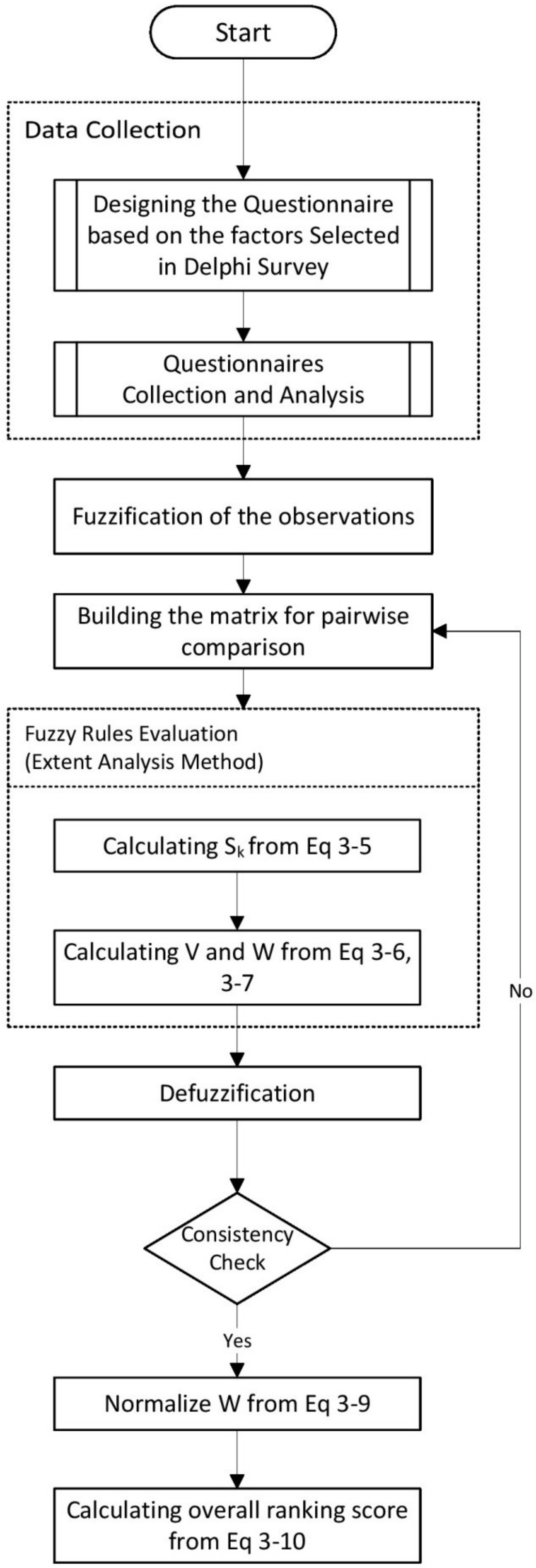


Figure 3-3.Flowchart for FAHP method

In Extent Analysis Method (EA), Consider $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$. The arithmetic functions are (Chang, 1996):

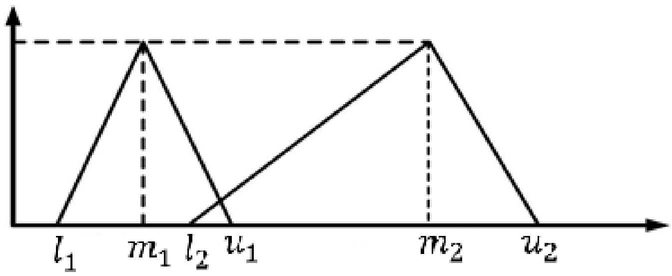


Figure 3-4.Triangular fuzzy numbers (Saaty, 1988)

$$M_1 + M_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad 3.2$$

$$M_1 \times M_2 = (l_1 \times l_2, m_1 \times m_2, u_1 \times u_2) \quad 3.3$$

$$M_1^{-1} = \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}\right), M_2^{-1} = \left(\frac{1}{u_2}, \frac{1}{m_2}, \frac{1}{l_2}\right) \quad 3.4$$

In this method, the triangular number of S_k is calculated for each row of the pairwise comparison matrix from below in which k is row number and i is criterion.

$$S_k = \sum_{i=1}^{n} M_{ki} \times \left[\sum_{k=1}^{n} \sum_{i=1}^{n} M_{ki}\right]^{-1} \quad 3.5$$

After computing S_k, their magnitude should be determined respect to others. The order of magnitude of M_1 respect to M_2 is:

$$\begin{cases} V(M_1 \geq M_2) = 1 & if\ m_1 \geq m_2 \\ V(M_2 \geq M_1) = \dfrac{u_1 - l_2}{(u_1 - l_2) + (m_2 - m_1)} & otherwise \end{cases} \quad 3.6$$

Equation 3-7 is used to find the weights of criteria in pairwise comparison matrix and Equation 3-8 shows the weight vector of criterion i:

$$W'(x_i) = Min\,\{V\,(S_i \geq S_k)\} \qquad k = 1,2, \dots, n \quad k \neq i \quad 3.7$$

$$W'(x_i) = [W'(c_1), W'(c_2), \dots, W'(c_n)]^T \quad 3.8$$

The result will be normalized from equation 3-9.

$$W_i = \frac{w_i'}{\sum w_i'} \quad 3.9$$

After finding acceptable results, the priority matrices are combined together by multiplying the weight of factors (W_i) and weight of sub-factors (Y_i), to calculate the overall scores (Saaty, 1988).

$$\text{Overall ranking score} = \sum_i^n W_i Y_i \quad 3.10$$

Following steps would ensure the consistency of the pairwise comparison matrix. Each triangular fuzzy number is replaced by the geometric average of its components. Then, the relative weight vector is calculated from normalized pairwise comparison matrix. After that, the pairwise comparison matrix is multiplied by relative weight vector and weighted sum matrix (WSM) is calculated. Ultimately the relative weight vector is divided by WSM and consistency vector is computed. λ_{max} is the average of the components of the consistency vector. Consistency index (CI) is degree of deviation from consistency. It is calculated as following in which n is the matrix size (Saaty, 1988).

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad 3.11$$

Moreover, consistency ratio (CR) is defined as the ratio of the consistency index (CI) for a set of judgments, divided by the random inconsistency index (RI) for random comparisons which is defined in Table 3-1 (Saaty, 1988).

$$CR = \frac{CI}{RI} \quad 3.12$$

Table 3-1.Random inconsistency indices (Saaty, 1988)

Number of Criteria	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

The concept of Shannon Entropy is important in Information theory and multi-criteria decision making as stated in section 2.6.3 and refers to an accepted measure of uncertainty and fuzziness. This is the main reason for choosing this method for calculating the weights. After analyzing the result from the Delphi method and identification of the important criteria from all the initial 30 factors, the experts were asked to choose the significant parameters. Their responses were analyzed through Shannon Entropy and the following formula of Entropy is generally used to obtain the weights of each criterion (Lotfi & Fallahnejad, 2010):

$$E_i = S(P_1, P_2, \ldots, P_n) = -E_0 \sum_{i=1}^{n} P_i \ln(P_i) \qquad 3.13$$

The process of finding the weights of importance in Entropy is similar to FAHP in building the pairwise comparison matrix. After building the matrix, the following four steps are performed for each array:

$$A = \begin{vmatrix} 1 & W_{12} & \ldots & W_{1n} \\ W_{21} & 1 & \ldots & W_{2n} \\ \vdots & \vdots & 1 & \vdots \\ W_{n1} & W_{n2} & \ldots & 1 \end{vmatrix}$$

Step 1: Normalization; set $\overline{W_{ji}} = \frac{W_{ji}}{\sum_{j=1}^{n} W_{ji}}$ $j = 1, \ldots, n; i = 1, \ldots, n$

Step 2: Compute entropy E_i as $E_i = -E_0 \sum_{j=1}^{n} \overline{W_{ji}}\, ln\, \overline{W_{ji}}$ $i = 1, \ldots, n$ where E_0 is the entropy constant and is $\frac{1}{\ln(n)}$.

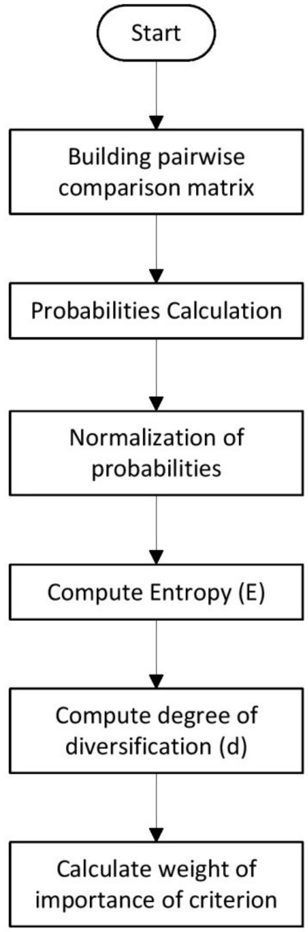


Figure 3-5.Flowchart of Shannon Entropy method

Step 3: Set $d_i = 1 - E_i$ as the degree of diversification.

Step 4: Calculate $w_i = \frac{d_i}{\sum_{i=1}^{n} d_i}, \ i = 1, \ldots, n$ as the weight of importance.

Figure 3-5 illustrates the calculation steps for Shannon Entropy. After finding the weights of importance from FAHP (w_j), they can be combined with computed degree of importance from Entropy (y_j) using equation below.

$$W_j = \frac{y_j w_j}{\sum_{j=1}^{n} y_j w_j} \qquad \forall j \tag{3.14}$$

3.3.3. Condition Index

After finding the weights of importance from FAHP and Entropy, the weights are employed to find the condition. The schematic steps of finding the condition index are illustrated in Figure 3-6. The whole process of model development is done through Microsoft Excel since it is an easy tool to handle the data. The selected factors are classified based on the range of available data and the effect of each class on deterioration is determined through previous literature. After finding the effect of each class of factors on deterioration, the linguistic terms of extremely low to extremely high is translated into numbers based on the scale presented in Figure 3-7 which is calculated form normal distribution to determine the Attribute Effects (AEs) of the classes.

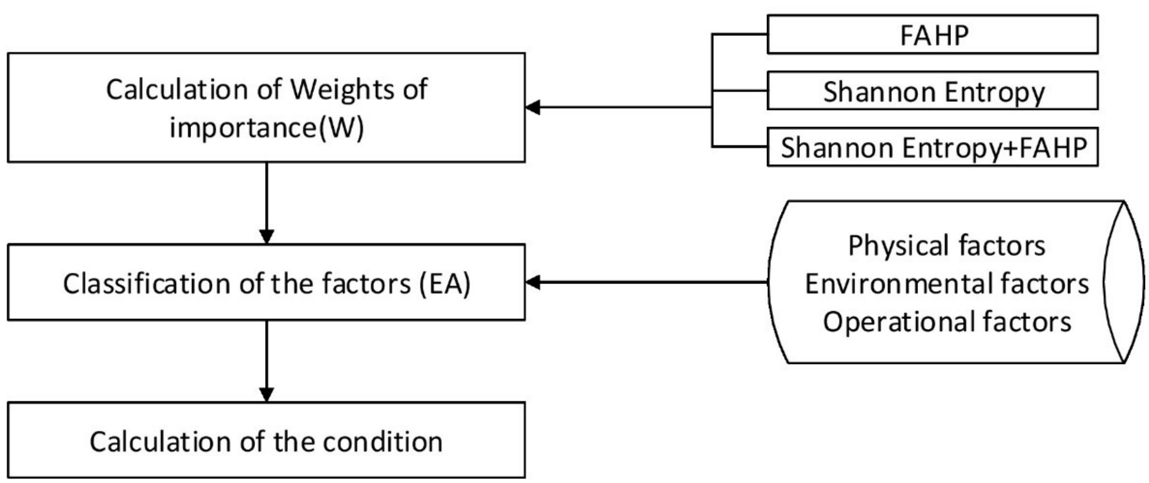


Figure 3-6.Flowchart of condition Index

Table 3-2.Classification of pipe wall thickness

factor performance		Impact	
If wall thickness is	<10 mm	then the chance of deterioration is	high
If wall thickness is	10 mm - 15 mm	then the chance of deterioration is	medium
If wall thickness is	15 mm - 20 mm	then the chance of deterioration is	very low
If wall thickness is	> 20 mm	then the chance of deterioration is	extremely low

Table 3-3.Classification of pipe age

factor performance		Impact	
If age is	< 20 yrs	then the chance of deterioration is	extremely low
If age is	20 yrs - 40 yrs	then the chance of deterioration is	very low
If age is	40 yrs - 60 yrs	then the chance of deterioration is	low
If age is	60 yrs - 80 yrs	then the chance of deterioration is	medium
If age is	80 yrs - 100 yrs	then the chance of deterioration is	high
If age is	100 yrs - 120 yrs	then the chance of deterioration is	very high
If age is	> 120 yrs	then the chance of deterioration is	extremely high

Table 3-4.Classification of pipe lining and coating (Fares, 2008)

factor performance		Impact	
If pipe has	Lining and coating	then the chance of deterioration is	medium
If pipe has	None	then the chance of deterioration is	extremely low

Table 3-5.Classification of pipe material (Fares, 2008)

factor performance		Impact	
If pipe material is	Concrete	then the chance of deterioration is	medium
If pipe material is	Asbestos	then the chance of deterioration is	high
If pipe material is	PVC	then the chance of deterioration is	very low
If pipe material is	Polyethylene (PE)	then the chance of deterioration is	extremely low
If pipe material is	Ductile Iron (DI)	then the chance of deterioration is	very low
If pipe material is	Steel	then the chance of deterioration is	very low
If pipe material is	Cast Iron (CI)	then the chance of deterioration is	very high

Table 3-6.ClassIfication of pipe installation

factor performance		Impact	
If pipe installation is	Poor	then the chance of deterioration is	extremely high
If pipe installation is	Moderate	then the chance of deterioration is	medium
If pipe installation is	Well	then the chance of deterioration is	extremely low

Table 3-7.Classification of Seismic activity

factor performance		Impact	
if seismic activity is	Low	then the chance of deterioration is	extremely low
if seismic activity is	Moderate	then the chance of deterioration is	medium
if seismic activity is	High	then the chance of deterioration is	high
if seismic activity is	Very high	then the chance of deterioration is	extremely high

Table 3-8.Classification of dissimilar metal

factor performance		Impact	
If dissimilar metal	is used in network	then the chance of deterioration is	medium
If dissimilar metal	is not used in network	then the chance of deterioration is	extremely low

Table 3-9.ClassIfication of bedding soil type

factor performance		Impact	
If bedding soil is	very lightly deteriorative	then the chance of deterioration is	extremely low
If bedding soil is	lightly deteriorative	then the chance of deterioration is	very low
If bedding soil is	moderately deteriorative	then the chance of deterioration is	medium
If bedding soil is	highly deteriorative	then the chance of deterioration is	very high
If bedding soil is	very highly deteriorative	then the chance of deterioration is	extremely high

Table 3-10.Classification of backfill material

factor performance		Impact	
If Backfill material is	very lightly deteriorative	then the chance of deterioration is	extremely low
If Backfill material is	lightly deteriorative	then the chance of deterioration is	very low
If Backfill material is	moderately deteriorative	then the chance of deterioration is	medium
If Backfill material is	highly deteriorative	then the chance of deterioration is	very high
If Backfill material is	very highly deteriorative	then the chance of deterioration is	extremely high

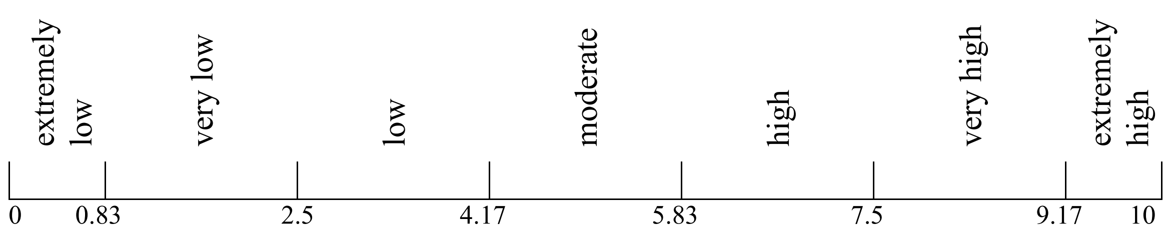
Table 3-11.Classification of water pressure

factor performance		Impact	
If water pressure is	Low	then the chance of deterioration is	very low
If water pressure is	Moderate	then the chance of deterioration is	medium
If water pressure is	High	then the chance of deterioration is	very high

Table 3-12.Classification of leakage (Fares, 2008)

factor performance		Impact	
if leakage is	very low	then the chance of deterioration is	extremely low
if leakage is	Low	then the chance of deterioration is	very low
if leakage is	Medium	then the chance of deterioration is	medium
if leakage is	high	then the chance of deterioration is	very high
if leakage is	very high	then the chance of deterioration is	extremely high

Figure 3-7.Equivalent range of Attribute Effect



The impact of each classification in previous tables are normalized based on Figure 3-7 and an attribute effect (AE) value is assigned to each linguistic term. The associated values are summarized in Table 3-13.

Table 3-13.Average Attributes Effect (AE_i) Value for criteria

Factors	AE_i	Factors	AE_i
1.Physical Factors		**2.Environmental Factors**	
1.1.Pipe material		**2.1. Bedding soil type**	
Concrete	5.01	Very lightly deteriorative	0.42
Asbestos	6.68	Lightly deteriorative	1.67
PVC	1.67	Moderately deteriorative	5.01
Polyethylene (PE)	0.42	Highly deteriorative	8.35
Ductile Iron (DI)	1.67	Very highly deteriorative	9.59
Steel	1.67	**2.2. Backfill material**	
Cast Iron (CI)	8.35	Very lightly deteriorative	0.42
1.2. Pipe wall thickness		Lightly deteriorative	1.67
<10	6.68	Moderately deteriorative	5.01
10 to 15	5.01	Highly deteriorative	8.35
15 to 20	1.67	Very highly deteriorative	9.59
>20	0.42	**2.3. Seismic activity**	
1.3. Pipe age		None	0.42
<20	0.42	Low	5.01
20 to 40	1.67	Medium	6.68
40 to 60	3.34	High	9.59
60 to 80	5.01		
80 to 100	6.68	**3. Operational Factors**	
100 to 120	8.35	**3.1. Water pressure**	
>120	9.59	Low	1.67
1.4. Pipe lining and coating		Moderate	5.01
No	5.01	High	8.35
Yes	0.42	**3.2. Leakage**	
1.5. Dissimilar metals		Very low	0.42
No	0.42	Low	1.67
Yes	5.01	Medium	5.01
1.6. Pipe installation		High	8.35
Poor	9.59	Very high	9.59
Moderate	5.01		
Well	0.42		

The condition index is calculated through equation 3-15 by summing the multiplication of the weight of each factor and the attribute effect associated to that factor.

$$Condition\ Index = \sum_{i=1}^{n} AE_i W_i \qquad 3.15$$

The model is validated by overlaying the final condition index lists and inspection results and checking whether the leakage points are in critical states or not.

3.4. Remaining useful life model

In this section, Artificial Neural Network is applied to estimate expected remaining useful life of the pipelines. Neural network is mostly used for approximation of unknown functions. It is capable to cover non-linear and complex behavior of water networks and is able to handle numerous variables which increase system performance reliability (Lawrence 1994). The overall flowchart of model development is presented in Figure 3-8. As described in literature review, the key feature of ANN is its learning ability. It can be trained by some examples to find the fairly accurate relation between inputs and outputs. Besides, ANN predicts the outputs for new inputs. In this research, ANN models were developed, trained, validated and tested in MATLAB 2014a with database of Montreal. Dataset was randomly divided into 70%, 15% and 15% groups which were used for training, validation and testing the results respectively. Several ANN models were developed which are divergent in three aspects of number of neurons in hidden layer which varies between 10 and 40, random groups of datasets and number of hidden layers which varies between one and two. Schematic illustration of the ANN network is illustrated in Figure 3-9.

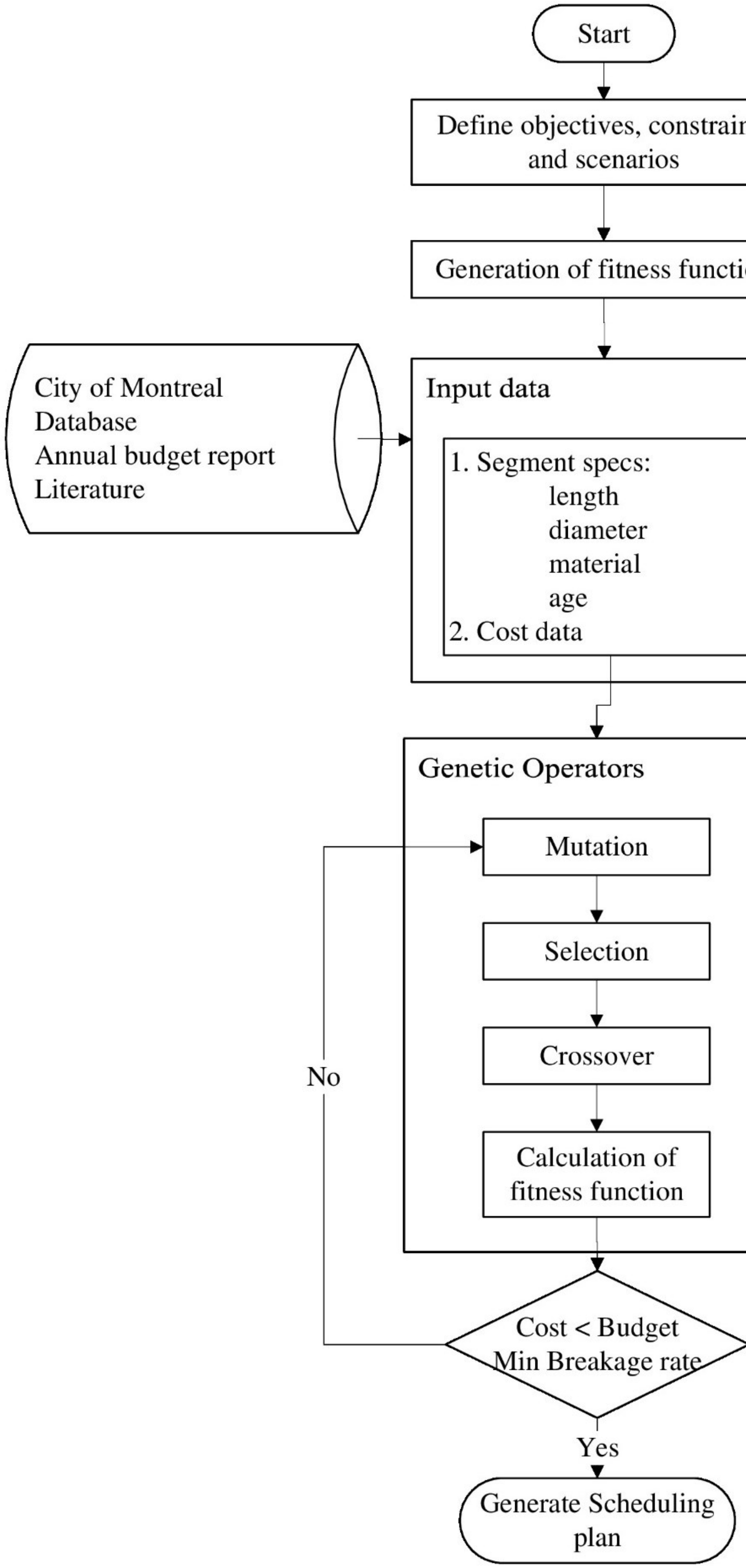


Figure 3-8. Model development framework

Figure 3-9.Structure of the ANN models; N_n and N_m are the numbers of neurons

Pipe material (M), diameter (D), length (L), condition (C) and breakage rate (BR) represent the selected input parameters from Montreal database, whereas the remaining useful life represents the estimated output parameter which is estimated form pipe age (A). Based on the pipe age data in database of City of Montreal, the average estimated age for pipeline is 150 years. Therefore, the estimated remaining useful life of the pipelines (target value) will be calculated considering 150 years as the ultimate age of a pipe.

$$Target\ value\ =\ 150 - pipe\ age \qquad 3.16$$

Levenberg–Marquardt, Bayesian Regularization and Scaled Conjugate Gradient algorithms were used for training of data. Levenberg–Marquardt is well-known for prediction, estimation and solving non-linear least squares fitting problems, while Bayesian Regularization are commonly used in noisy and small problems. The algorithms attempted to minimize the sum of squared errors by updating the network's bias and weight. Training sets are used to adjust the network structure based on the associated errors until it reaches the best structure. Validation sets are utilized to measure network generalization capabilities and to pause training when generalization stops improvement. After training, testing sets will provide an independent index of the network performance. For each ANN model, trials were performed to reach the lowest error. The performance of the models was assessed based on R^2, mean absolute error (MAE), relative absolute error (RAE), root relative square error (RRSE) and mean absolute percentage error (MAPE) according to the following equations. t_i is the target value while o_i is the output value

$$R^2 = 1 - \frac{\sum_i (t_i - o_i)^2}{\sum_i \left(t_i - \frac{1}{n}\sum_i t_i\right)^2} \tag{3.17}$$

$$MAE = \frac{1}{n}\sum_i |t_i - o_i| \tag{3.18}$$

$$RAE = \frac{\sum_i |t_i - o_i|}{\sum_i \left|t_i - \frac{1}{n}\sum_i t_i\right|} \tag{3.19}$$

$$RRSE = \sqrt{\frac{\sum_i (t_i - o_i)^2}{\sum_i \left(t_i - \frac{1}{n}\sum_i t_i\right)^2}} \tag{3.20}$$

$$MAPE = \frac{100}{n}\sum_i \frac{|t_i - o_i|}{t_i} \tag{3.21}$$

The coefficient of determination (R^2) is used in statistical analysis repeatedly since it is easy to calculate and understand. It oscillates among [0, 1] and evaluates the percentage of total differences between estimated and target values with respect to the average. MAE is an absolute measure and ranges from 0 to + ∞. One advantage of MAE is that it is not affected by outliers and can be calculated as an alternative for mean square error (MSE). RAE is less influenced by outliers same as MAE, however it is contaminated by extremely large or small values. The relative absolute error (RAE) and root relative square error (RRSE) assess the performance of a forecasting model in the same way (Makridakis and Hibon 1995). In fact, lower RAE and RRSE result in better performance of the forecasting model. In recent researches, MAPE is mostly used to evaluate the accuracy of a model due to its simplicity. It identifies error as a proportion of actual data and higher accuracy comes with lower MAPE. This index can be divided into four indicators: high accuracy forecast

(MAPE < 10%), sound forecast (10% < MAPE < 20%), feasible forecast (20% < MAPE < 50%), and error forecast (MAPE > 50%) (Jia et al. 2015).

3.5. Budget allocation model

The overall flowchart of model development through Genetic Algorithm is presented in Figure 3-10. As stated in literature review, Genetic Algorithm is frequently used for optimization. In this study, it is used to optimize the allocation of a constrained budget for rehabilitation and replacement strategies of an assumed water network distribution. The budget for rehabilitation strategies is constrained and allocated based on the municipal decisions and policies. It should be spent thoroughly each year since any outstanding balance would not be transferred to the upcoming year.

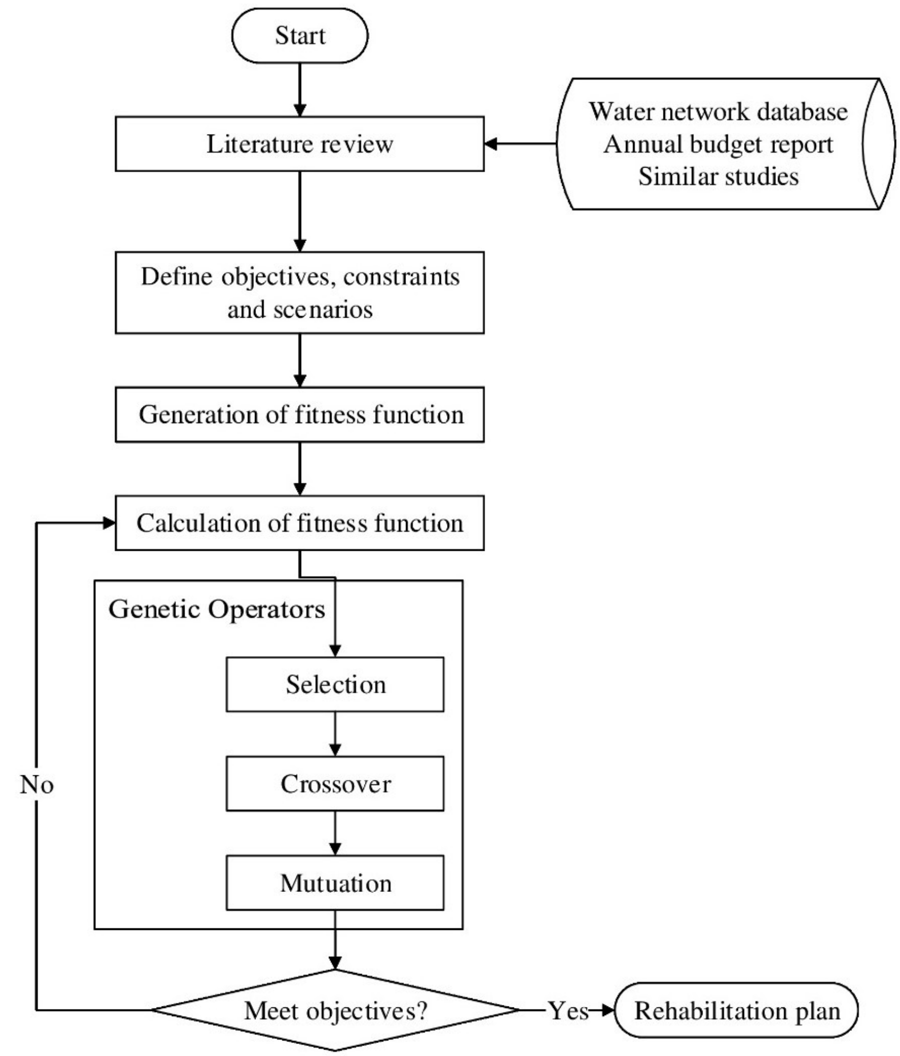


Figure 3-10. Model development framework

Therefore, the problem this model seeks to solve is as follows: "assume a water distribution network with n individual pipes and $K_{i,t}$ $(i \in [1, n])$ is the predicted number of breaks for pipe i in year t. Given a planning horizon of T years and a yearly constrained budget of B for maintenance and rehabilitation, how should the pipes be scheduled for maintenance in order to exhaust the whole allocated budget?"

The budget considered for this kind of analysis could be selected from three different classes of budget: 1) annually constrained budget which is the annual budget allocated to the water distribution network, is constant for each year and is estimated in municipal meetings, 2) globally constrained budget which is the global budget allocated for the water network over its expected life which is the sum of all costs during the years of operation and 3) unconstrained which is rarely noticed through the literature.

Therefore, the objective of this model is to maximize the use of budget and allocate funds in the way that the difference of total cost of rehabilitation and replacement of the pipelines and budget becomes negligible. Furthermore, it seeks to assign budget based on not only time but also size and failure prediction. However, total cost should be less than the allocated budget. Therefore, the fitness function will be

$$Budget - C_{total} \geq 0$$

The total cost of pipe rehabilitation timing is directly affected by cost of failure repair, cost of direct/indirect damage, water loss and social cost on one hand and cost of time on the other hand. Social cost is the cost of closing the street and increasing traffic jams. The available scenarios for each pipe is

1. Replacement
2. Rehabilitation
    a. Open trench (major)
    b. Trenchless (minor)
3. No action upon breakage or leakage (Leave as is)
4. Does not need any rehabilitation

For each scenario, there is a cost associated to that scenario which should be considered in the budget allocation. These costs are cost of failure repair, social cost, cost of water loss and cost of pipe replacement which is assumed to have two components of mobilization cost and the length-unit cost as described in Table 3-14 and Table 3-15. The mobilization costs covers cost of setting up the job site, signage, discovery and marking of adjacent infrastructure while Cr_i depends on pipe material and diameter (Nafi and Kleiner, 2009).

Table 3-14. Mobilization cost data

Item	M	$C_i^{repair\ major}$	$C_i^{repair\ minor}$	$C_i^{water\ loss}$	C_i^{social}
Value ($)	2000	5000	3000	100	2500

Table 3-15. Replacement cost

Diameter (mm)	150	200	250	300	400	500	600
$Cr_i\ (\frac{\$}{m})$	350	360	380	410	500	730	900

Cost of water loss or non-revenue water has been ignored historically in North America. There are several reason linked to this problem. Significant ones are related to the fact that there is little government regulation of water loss in most states and the fact that the value of water is taken for granted for years by both the consumers and the infrastructure system managers. In this study the cost of water loss due to aging and inadequate infrastructure has been taken into account for budget allocation strategies.

GA solves optimization problems through a gradual evolutionary approach in which best solutions of each step is used as leaders to find the best solution of the problem. Thus, the final solution is a winner over others. GA consists of two separate phases; in first one the individuals are evaluated based on their fitness function and in the other one individuals are evolved with genetic operators of selection, crossover and mutation toward the best solution. In this research, the GA model was developed in MATLAB 2014a. Initial number of population is assigned to 10 and the percent of crossover and mutation set to be 0.8 and 0.2 respectively. Two-point crossover was used to mix the parents and produce the new generation. Also the maximum number of iteration set to be 20 because it shows good accuracy optimizing the cost.

CHAPTER 4: DATA COLLECTION AND ANALYSIS

4.1. Chapter overview

Chapter 4 is about data collection and the related modification to prepare it for being used in the analysis. The sources of data in this study are summarized in literature, data related to city of Montreal and two series of collected questionnaire from experts. Literature (section 4.2.1) covers the data collected from official municipal reports posted on city of Montreal website and several related journal papers which have discussed the optimization of budget allocation in water distribution network. Afterwards, the historical data about the water distribution network of city of Montréal is explained in section 4.2.2. This data is used in the modeling of a case study to develop and validate the model to see whether the proposed model works properly or not. Section 4.2.3 discussed two series of questionnaires which both sought expert's opinions about factors influencing deterioration and condition. The demographic distribution of the participants and their year of expertise are explained in this section.

4.2. Sources of data collection

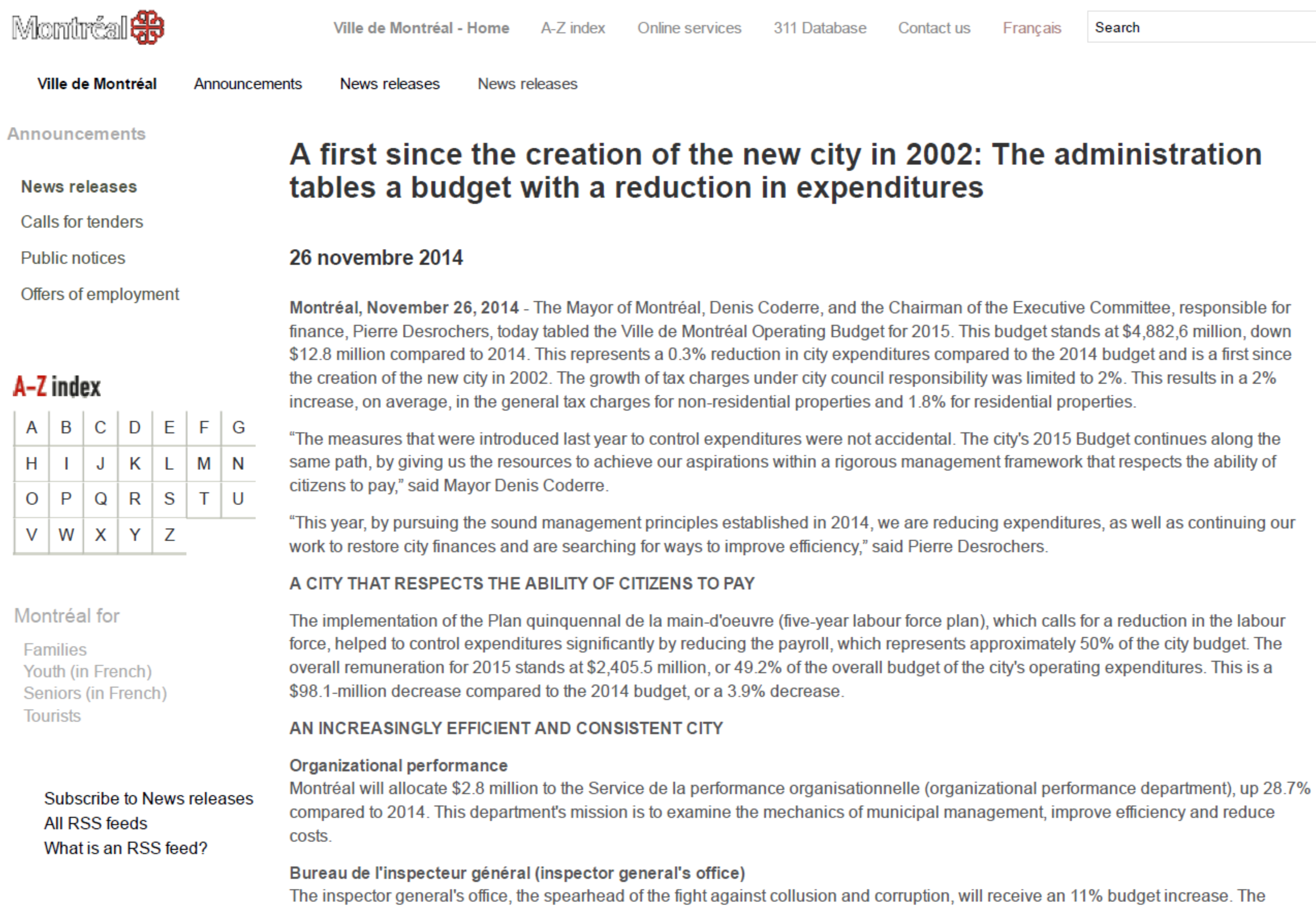
4.2.1. Literature

The report of office of the Mayor and Executive Committee on November 26th, 2014 has elaborated the budget priorities for city of Montreal for 2015. As indicated in this report, water infrastructure and management are among the top priorities: "*The overall budget for water management stands at $376.9 million. We are allocating $61.8 million for wastewater treatment, up 1.2% compared to the previous budget. A sum of $56.7 million* *will be allocated to drinking water supply and treatment, while $82.3 million will go for expenditures associated with the drinking water distribution network. We are staying the course with regards to maintenance, repair and optimization of secondary sewer networks and investing more than $50.3 million."* Therefore, the overall budget for water management is about $376.9 million. A sum of $56.7 million will stand for drinking water supply and treatment, while $82.3 million will be allocated to the drinking water distribution network. This portion of money will be used as the annual budget for renewal and rehabilitation plans in this research. The full report is displayed in Appendix C at the end of this report.

Furthermore, Nafi and Kleiner (2009) did a complete research about efficient scheduling for renewal of water pipes in a predefined planning period. They considered cost of failure as a summation of costs of replacement, direct, indirect, social, and water loss and calculated an average amount for each cost. This study is an appropriate reference for estimation and analysis, although it was prepared a couple of years ago. The costs were modified based on the inflation rate and current market value p the maintenance and replacement plans.

Table 4-1. Cost data (Nafi and Kleiner, 2009)

Item	Unit	Value
Pipe Replacement : 150 mm	$/m	300
Pipe Replacement : 200 mm	$/m	350
Mobilization cost	$	2000
Cost of water loss	$	100
Average social cost	$	3000



Montréal

Ville de Montréal - Home | A-Z index | Online services | 311 Database | Contact us | Français | Search

Ville de Montréal | Announcements | News releases | News releases

Announcements

News releases
Calls for tenders
Public notices
Offers of employment

A-Z index

A	B	C	D	E	F	G
H	I	J	K	L	M	N
O	P	Q	R	S	T	U
V	W	X	Y	Z		

Montréal for

Families
Youth (in French)
Seniors (in French)
Tourists

Subscribe to News releases
All RSS feeds
What is an RSS feed?

A first since the creation of the new city in 2002: The administration tables a budget with a reduction in expenditures

26 novembre 2014

Montréal, November 26, 2014 - The Mayor of Montréal, Denis Coderre, and the Chairman of the Executive Committee, responsible for finance, Pierre Desrochers, today tabled the Ville de Montréal Operating Budget for 2015. This budget stands at $4,882,6 million, down $12.8 million compared to 2014. This represents a 0.3% reduction in city expenditures compared to the 2014 budget and is a first since the creation of the new city in 2002. The growth of tax charges under city council responsibility was limited to 2%. This results in a 2% increase, on average, in the general tax charges for non-residential properties and 1.8% for residential properties.

"The measures that were introduced last year to control expenditures were not accidental. The city's 2015 Budget continues along the same path, by giving us the resources to achieve our aspirations within a rigorous management framework that respects the ability of citizens to pay," said Mayor Denis Coderre.

"This year, by pursuing the sound management principles established in 2014, we are reducing expenditures, as well as continuing our work to restore city finances and are searching for ways to improve efficiency," said Pierre Desrochers.

A CITY THAT RESPECTS THE ABILITY OF CITIZENS TO PAY

The implementation of the Plan quinquennal de la main-d'oeuvre (five-year labour force plan), which calls for a reduction in the labour force, helped to control expenditures significantly by reducing the payroll, which represents approximately 50% of the city budget. The overall remuneration for 2015 stands at $2,405.5 million, or 49.2% of the overall budget of the city's operating expenditures. This is a $98.1-million decrease compared to the 2014 budget, or a 3.9% decrease.

AN INCREASINGLY EFFICIENT AND CONSISTENT CITY

Organizational performance
Montréal will allocate $2.8 million to the Service de la performance organisationnelle (organizational performance department), up 28.7% compared to 2014. This department's mission is to examine the mechanics of municipal management, improve efficiency and reduce costs.

Bureau de l'inspecteur général (inspector general's office)
The inspector general's office, the spearhead of the fight against collusion and corruption, will receive an 11% budget increase. The

Figure 4-1. Budget report of city of Montreal, page 1 budget stands at $5.6 million in 2015.

Borough financing reform
In an effort to make the city more consistent, and to improve municipal services in the boroughs, the administration announced the introduction of the borough financing reform. This reform will be implemented progressively and result in a $3.7-million annual increase of borough budgets, or $18.6 million over five years.

A CITY WORKING FOR MONTREALERS

Priority to public transit
The city's contribution to public transit stands at $485.9 million, an increase of $30 million compared to 2014. The portion of the budget dedicated to the regular contribution to the Société de transport de Montréal stands at $409.1 million, up $25 million compared to the previous year. The Agence métropolitaine de transport will receive a contribution of $63.6 million, or $8.5 million more than in 2014, to cover the costs associated with the eastern commuter train.

Increased investment in infrastructure
In order to make up for delays in infrastructure repair, the administration implemented the Programme montréalais d'immobilisations (Montréal capital works program), which plans investment needs for the next ten years. To meet program guidelines, the 2015 Budget plans to increase temporarily debt financing by close to $1 billion over five years and also increase cash payment of capital expenditures by $40 million.

Road network and snow removal
A budget of $374.4 million has been earmarked for road network management, an increase of $10.4 million, or 2.8%, compared to 2014. Of this amount, $155.7 million will be allocated to snow removal. The budget for roads has been increased by more than $4 million, for a total of $136.4 million, including $4.2 million to repair potholes and cracks. A budget of $45 million has been allocated for work involving traffic and parking.

Water management
The overall budget for water management stands at $376.9 million. We are allocating $61.8 million for wastewater treatment, up 1.2% compared to the previous budget. A sum of $56.7 million will be allocated to drinking water supply and treatment, while $82.3 million will go for expenditures associated with the drinking water distribution network. We are staying the course with regards to maintenance, repair and optimization of secondary sewer networks and investing more than $50.3 million.

Economic development
A sum of $13 million has been allocated to the Success@Montréal program, to promote economic development. This represents a $2-million increase compared to the previous budget.

Waste management
A budget of $163.4 million has been earmarked for waste management (household waste and recyclables).

Environmental projects
A budget of $12.7 million has been earmarked for environmental projects, up 2.6% compared to 2014. This will be used to combat air,

Figure 4-2.Budget report of city of Montreal, page 2

This data is used in this research not only to generate missing data but also as the input for implemented models. The unit cost of pipe replacement for other diameters ($/m) have been generated along with other costs (e.g. direct, indirect, minor and major rehabilitation) in order to determine the best rehabilitation and replacement strategy.

4.2.2. City of Montreal, Quebec, Canada

Due to the scarcity of historical data, it is approximately impossible to find a complete database which includes all the specifications of a water distribution networks. Since one of the limitation of previous models is relatively small database, efforts were done to find a large database. Therefore, water distribution network of city of Montreal was selected for analysis since it is large enough for the analysis. This database was extracted from Geographic Information System (GIS) shapefile of city of Montreal and imported to Excel worksheets. The water network of city of Montreal is shown in Figure 4-3. It consists of 125,829 data points which covers all over the Island of Montreal with the total length of 5340.2 km. The network consists of eight different pipe materials including Cast iron (CI), Ductile iron (DI), PVC, PE, asbestos cement, concrete, stainless steel and copper. It also includes data about installation and rehabilitation dates, diameter, owner of pipes, length and rehabilitation type. There are 11,645 breaks all over the network from the initial installation date with breakage rate ranging from 0.017 to 1098.92 breaks per year per meter. A summary of the available quantitative data of this dataset is given in

Table 4-2 and brief description of qualitative data are shown in Table 4-3.

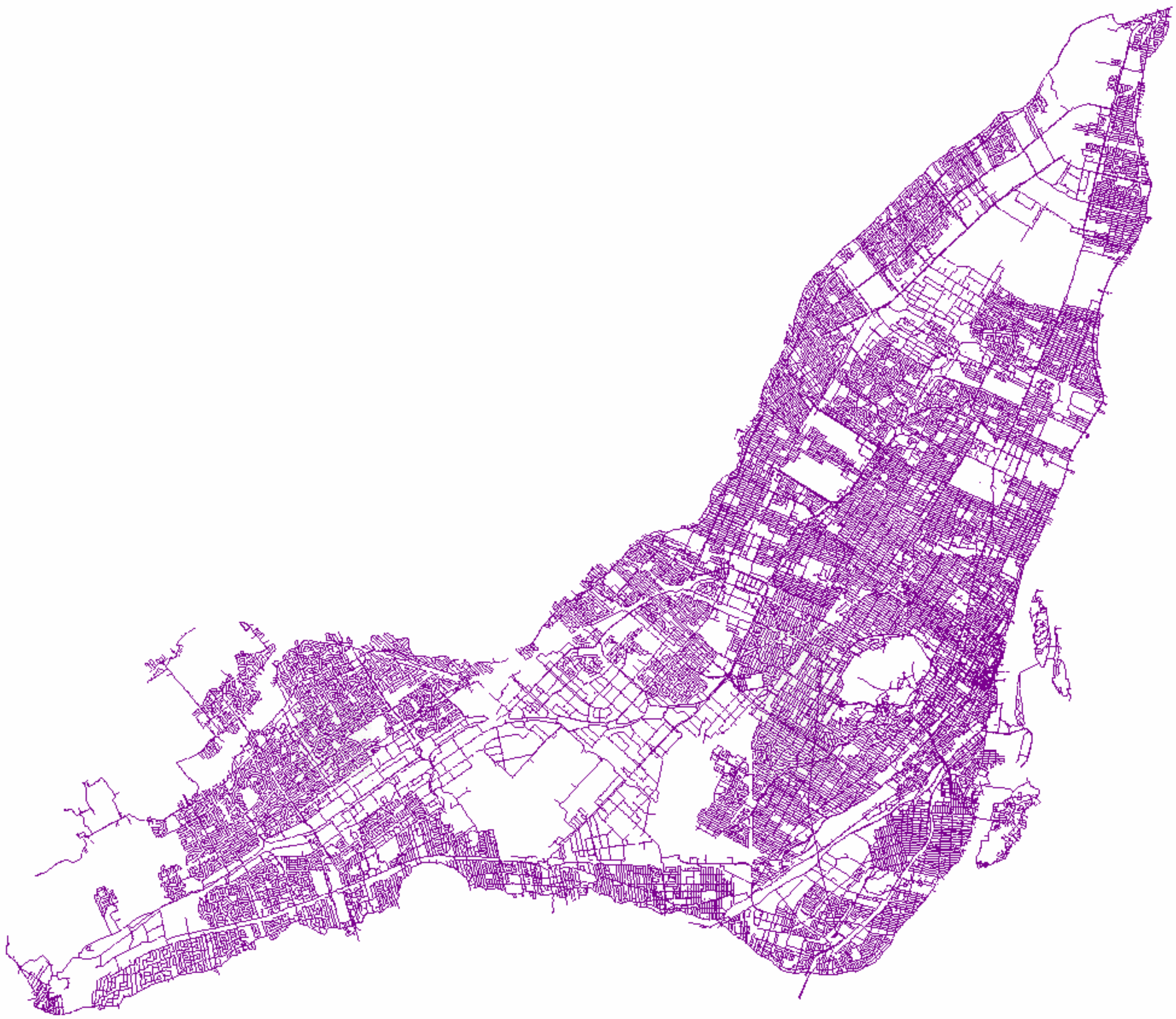


Figure 4-3. Water network of City of Montreal

Table 4-2. Quantitative data attributes for water network, City of Montreal

Attribute	Min	Max	Mean	Standard deviation	Mode
Installation date	1862	2014	1961.47	31.29	1955
Rehabilitation date	1914	2014	2004.38	11.98	2011
Diameter (mm)	20	3900	245.63	151.89	200
Length (m)	0.15	6557.65	43.31	65.17	0.15
Breakage Rate (breaks/year/m)	0	1098.92	0.17	6.05	0

aqu_segment

NUMEROSE_4	NUMEROSE_5	OBJECTID	PROPRIETAI	PROPRIET_1	PROVENANCE	REMARQUE	RESERVOIR_	RESERVOIR1	STATUTDESC	STATUTGEOM	STATUT_R
	NA	10497474	VDM-VM	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	E
	NA	10497475	VDM-VM	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	E
	NA	10497476	VDM-VM	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	E
	NA	10497477	VDM-PM	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	E
	NA	10497478	VDM-PM	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	E
	NA	10497479	VDM-VM	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	E
	NA	10497480	VDM-PM	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	E
	NA	10497481	VDM-PM	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	E
	NA	11201266	PC	GE_CGV	ML		PCLS	GE_DPEP	AC	AC	E
	NA	11201267	PC	GE_CGV	ML		PCLS	GE_DPEP	AC	AC	E
	NA	10497485	VDM-VM	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	E
	NA	10497487	VDM-VM	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	A
	NA	10497488	P	GE_PA	CA		INC	NA	AC	AC	E
	NA	10497489	VDM-VM	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	E
	NA	10059850	VDM-MH	GE_CGV	CA		MCTA	GE_DPEP	AC	AC	E
	NA	10059852	VDM-MH	GE_CGV	CA		MCTA	GE_DPEP	AC	AC	E
	NA	10059853	VDM-MH	GE_CGV	CA		MCTA	GE_DPEP	AC	AC	E
	NA	10059854	VDM-MH	GE_CGV	CA		MCTA	GE_DPEP	AC	AC	E
	NA	10059855	VDM-MH	GE_CGV	CA		MCTA	GE_DPEP	AC	AC	E
	NA	10059856	VDM-MH	GE_CGV	CA		MCTA	GE_DPEP	AC	AC	E
	NA	10059857	VDM-MH	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	E
	NA	10059858	VDM-MH	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	E
	NA	11201281	VDM-LN	GE_CGV	PR	MAJ_2974	VNDI	GE_DPEP	AC	AC	E
	NA	11201309	VDM-LN	GE_CGV	PR	MAJ_2066	VNDI	GE_DPEP	AC	AC	E
	NA	11201310	VDM-LN	GE_CGV	PR	MAJ_2066	VNDI	GE_DPEP	AC	AC	E
	NA	11201311	VDM-LN	GE_CGV	PR	MAJ_2066	VNDI	GE_DPEP	AC	AC	E
	NA	11201268	PC	GE_CGV	ML		PCLS	GE_DPEP	AC	AC	E
	NA	10060734	VDM-MH	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	E
	NA	10060735	VDM-MH	GE_CGV	CA		MCTA	GE_DPEP	INC	INC	E

STATUT_R_M	TYPEPROTEC	TYPEPROT_1	TYPEREHAB_	TYPEREHAB1	TYPESEGMEN	TYPESEGM_1	NOTRCGEO_1	timestamp	OBJECTID_1	SHAPE_Leng
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	1	0.511716
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	2	6.136686
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	3	6.615236
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	4	0.914786
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	5	2.193501
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	6	0.924705
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	7	0.636796
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	8	2.455663
GE_PB	NA	NA	NA	NA	BD	GE_AV	GE_CGV	12/28/2014	9	3.860249
GE_PB	NA	NA	NA	NA	BD	GE_AV	GE_CGV	12/28/2014	10	2.5088
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	11	6.526202
GE_AV	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	12	4.072111
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	13	22.841583
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	14	12.218041
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	15	2.127527
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	16	0.371323
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	17	2.019393
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	18	0.200094
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	19	5.5936
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	20	6.580306
GE_PP	INC	NA	INC	NA	BDG	GE_PP	GE_CGV	12/28/2014	21	3.206322
GE_PP	INC	NA	INC	NA	BDG	GE_PP	GE_CGV	12/28/2014	22	0.937644
GE_PR	NA	NA	NA	NA	R	GE_PR	GE_CGV	12/28/2014	23	25.461271
GE_PR	NA	NA	NA	NA	BI	GE_PR	GE_CGV	12/28/2014	24	1.076075
GE_PR	NA	NA	NA	NA	BI	GE_PR	GE_CGV	12/28/2014	25	5.304192
GE_PR	NA	NA	NA	NA	R	GE_PR	GE_CGV	12/28/2014	26	92.967292
GE_PB	NA	NA	NA	NA	BD	GE_AV	GE_CGV	12/28/2014	27	4.27521
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	28	16.974465
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	29	0.85703
GE_PP	INC	NA	INC	NA	BD	GE_PP	GE_CGV	12/28/2014	30	5.455913

Figure 4-4. Sample GIS shapefile of city of Montreal

aqu_segment

FID	Shape *	OBJECTID_2	geodb_oid	CLASSESEGM	CLASSESE_1	CREEPAR_M	DATEABANDO	DATEABAN_1	DATECREEE_	DATEINSTAL
0	Polyline	1	1	INC	GE_NT	SG	<Null>	NA	8/9/2007	1/1/1911
1	Polyline	2	2	INC	GE_NT	SG	<Null>	NA	8/9/2007	1/1/1911
2	Polyline	3	3	INC	GE_NT	SG	<Null>	NA	8/9/2007	1/1/1900
3	Polyline	4	4	INC	GE_NT	SG	<Null>	NA	8/9/2007	1/1/1909
4	Polyline	5	5	INC	GE_NT	SG	<Null>	NA	8/9/2007	1/1/1988
5	Polyline	6	6	INC	GE_NT	SG	<Null>	NA	8/9/2007	1/1/1876
6	Polyline	7	7	INC	GE_NT	SG	<Null>	NA	8/9/2007	1/1/1890
7	Polyline	8	8	INC	GE_NT	SG	<Null>	NA	8/9/2007	1/1/1890
8	Polyline	9	9	INC	GE_NT	ubastyo	<Null>	NA	2/22/2012	4/6/1967
9	Polyline	10	10	INC	GE_NT	ubastyo	<Null>	NA	2/22/2012	4/6/1967
10	Polyline	11	11	INC	GE_NT	SG	<Null>	NA	8/9/2007	1/1/1912
11	Polyline	12	12	INC	GE_NT	SG	4/5/2012	GE_PP	8/9/2007	1/1/1872
12	Polyline	13	13	INC	GE_NT	SG	<Null>	NA	8/9/2007	1/1/1890
13	Polyline	14	14	INC	GE_NT	SG	<Null>	NA	8/9/2007	1/1/1891
14	Polyline	15	15	INC	GE_NT	MT	<Null>	NA	4/30/2007	1/1/1962
15	Polyline	16	16	INC	GE_NT	MT	<Null>	NA	4/30/2007	1/1/1962
16	Polyline	17	17	INC	GE_NT	MT	<Null>	NA	4/30/2007	1/1/1962
17	Polyline	18	18	INC	GE_NT	MT	<Null>	NA	4/30/2007	1/1/1962
18	Polyline	19	19	INC	GE_NT	MT	<Null>	NA	4/30/2007	1/1/1962
19	Polyline	20	20	INC	GE_NT	MT	<Null>	NA	4/30/2007	1/1/1962
20	Polyline	21	21	INC	GE_NT	MT	<Null>	NA	4/30/2007	1/1/1911
21	Polyline	22	22	INC	GE_NT	MT	<Null>	NA	4/30/2007	1/1/1911
22	Polyline	23	23	INC	NA	umuchbe	<Null>	NA	2/22/2012	11/1/2009
23	Polyline	24	24	INC	NA	umuchbe	<Null>	NA	2/22/2012	11/1/2009
24	Polyline	25	25	INC	NA	umuchbe	<Null>	NA	2/22/2012	11/1/2009
25	Polyline	26	26	INC	NA	umuchbe	<Null>	NA	2/22/2012	11/1/2009
26	Polyline	27	27	INC	GE_NT	ubastyo	<Null>	NA	2/22/2012	4/6/1967
27	Polyline	28	28	INC	GE_NT	SG	<Null>	NA	4/30/2007	1/1/1968

DATEINST_1	DATEINST_2	DATEINST_3	DATEMODIFI	DATEREHAB	DATEREHAB_	DECOUPAGE	DIAMETREIL	DIAMETREI_
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl0235_AQU		1016
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl0235_AQU		1016
P1000M	GE_PA	GE_NT	<Null>	<Null>	NA	31hl0235_AQU		1016
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl0235_AQU		1016
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl0235_AQU		1016
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl0235_AQU		1016
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl0235_AQU		1016
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl0235_AQU		1016
INC	NA	GE_PB	2/22/2012	<Null>	NA	COR_Pointe_Claire_20120222_YBV.dgn		508
INC	NA	GE_PB	<Null>	<Null>	NA	COR_Pointe_Claire_20120222_YBV.dgn		508
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl0235_AQU		1016
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl0235_AQU		508
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl0235_AQU		1016
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl0235_AQU		1016
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl1139_AQU		1016
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl1139_AQU		1524
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl1139_AQU		3048
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl1139_AQU		2540
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl1139_AQU		2032
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl1139_AQU		1524
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl1139_AQU		508
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl1139_AQU		508
P005M	GE_PR	GE_PR	2/22/2012	<Null>	NA	MAJ_2974_20120221_BM.dgn		2032
P005M	GE_PR	GE_PR	<Null>	<Null>	NA	MAJ_2974_20120221_BM.dgn		1524
P005M	GE_PR	GE_PR	2/22/2012	<Null>	NA	MAJ_2974_20120221_BM.dgn		1524
P005M	GE_PR	GE_PR	2/22/2012	<Null>	NA	MAJ_2066_20120221_BM.dgn		2032
INC	NA	GE_PB	2/22/2012	<Null>	NA	COR_Pointe_Claire_20120222_YBV.dgn		508
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl1237_AQU		762
P010M	GE_PA	GE_PA	<Null>	<Null>	NA	31hl1237_AQU		762

Figure 4-5. Sample GIS shapefile of city of Montreal (continued)

Table 4-3.Qualitative data attributes for water network, City of Montreal

Attribute	Classes	Percentage
Material	DI	29.61
	CI	56.07
	Asbestos	0.83
	Concrete	5.32
	Copper	0.05
	PVC	5.51
	PE	0.24
	Steel	0.62
	Unknown	1.75
Rehabilitation type	Slip-lining	35.28
	Bursting	34.87
	External coatings - Epoxy resin	2.61
	External coatings - Cement Mortar	22.65
	Reconditioned steel	4.58

4.2.3. Questionnaires

In this research, 2 set of questionnaires were sent to two different groups of experts. The former set is used to perform Delphi studies while the latter undertakes AHP and Shannon Entropy methods.

Questionnaire 1

The questionnaire was distributed on April 21st, 2014 and all the responses were collected in one week. The data collection process consisted of three rounds. In “classical Delphi”, the initial round begins with a set of flexible questions asking experts to generate ideas about the issue. However, in this study the questionnaire was pre-designed based on the provided factors in literature (National Guide to Sustainable Municipal Infrastructure, 2003). The questionnaire was designed in an online format on Qualtrics website which is a user-friendly data collection platform. The structure of the questionnaire consists of four parts: informed consent form, respondent’s information, parameters’ description and questions. The first three questions, the respondents are requested to rank the factors in physical, environmental and operational class based on their relative importance from "not at all important" to "extremely important". Second round began with sending the panelist's own completed questionnaire in previous step along with the average scores of the panel and asked them whether they would like to modify their responses. The panel's average score of the factor, each panelist's score of the factor in the previous round and comments of other panelists on the reason of their scoring are the feedback which group members receive in the second round. The analysis is performed for the second round and third round was started by sending back the questionnaires. In this study, third round was the final round because there was no change in the responses. Data about the participants in the survey is provided in Figure 4-6 to Figure 4-7. Figure 4-8 shows respondents' area of expertise.

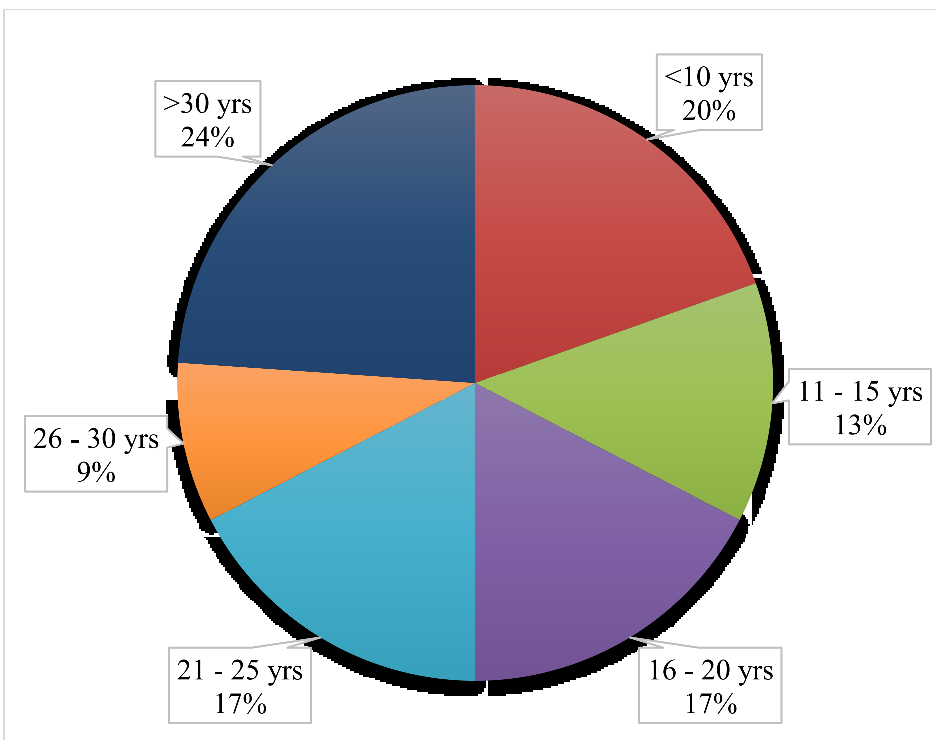


Figure 4-6.Years of experience of participants in the Delphi study

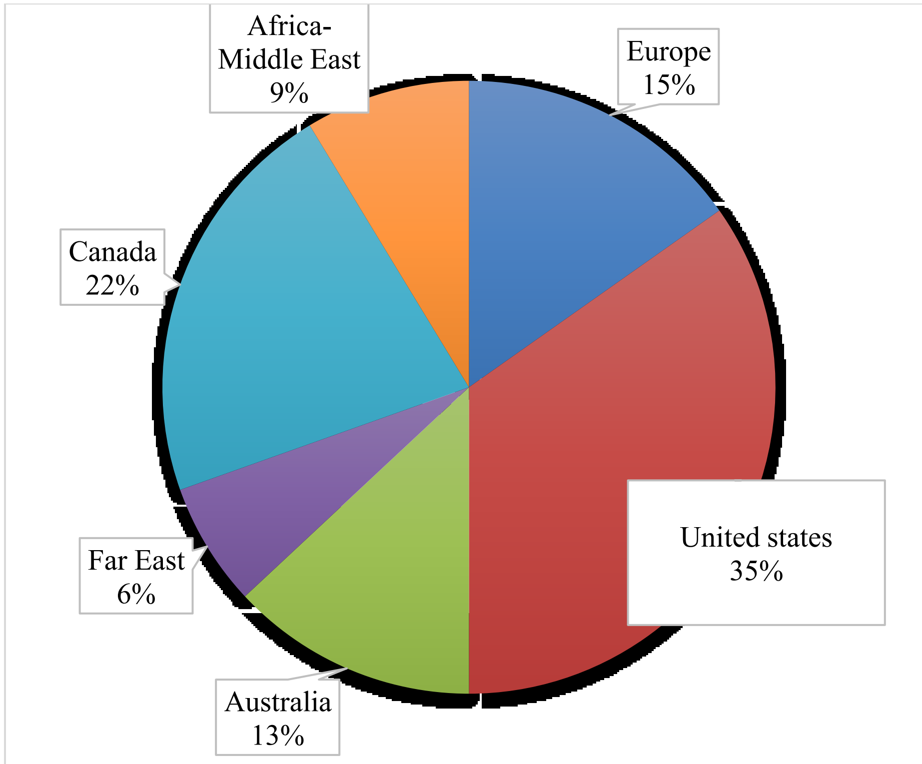


Figure 4-7.Demographic distribution of the experts

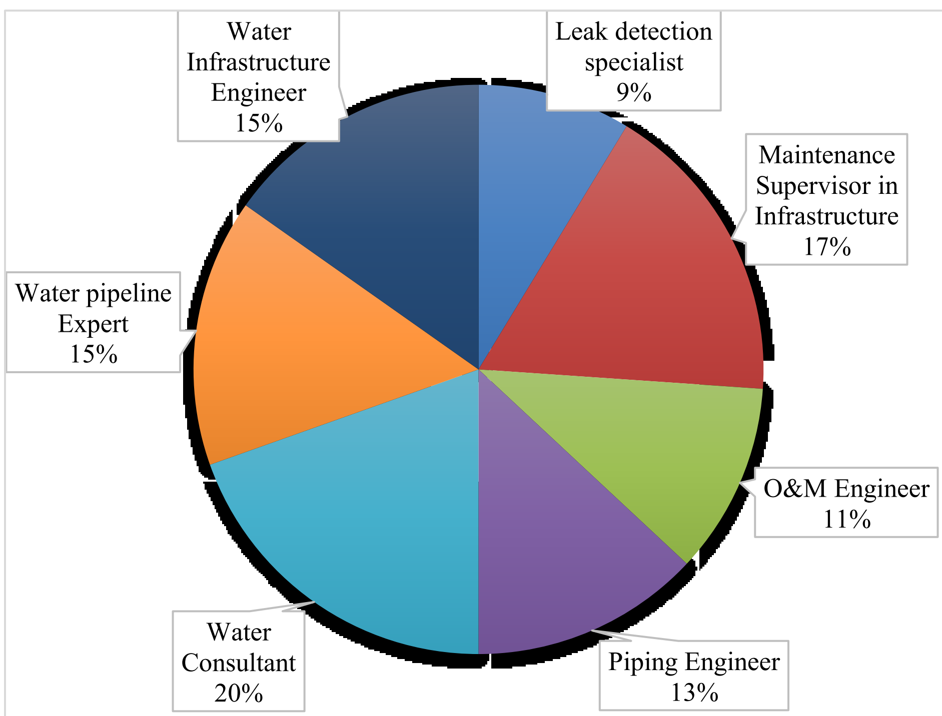


Figure 4-8. Expertise distribution of the experts

As stated previously, the main area of expertise of respondents could be divided into three groups of pipe, water and maintenance. The piping category consists of piping engineers and water pipeline experts. Water consultants and water infrastructure engineers are classified under water category and the rest which are leak detection specialists, O&M Engineers and Maintenance supervisors in infrastructure will be classified as maintenance category. The questionnaire is displayed in following figures.

The Delphi survey initial questionnaire

Informed Consent Form

This questionnaire aims at eliciting input on the factors that impact deterioration of water mains in distribution networks. The findings of this survey will be utilized in my PhD research on development of deterioration models for water distribution networks. It takes approximately 10 minutes to complete this questionnaire.

The factors are clustered in three groups; physical, environmental and operational. You are requested to rank these factors based on their relative importance in the first three questions. Sections 4 and 5 aim at the same target. If you would like to receive a copy of the findings of this questionnaire, please mark the appropriate box below.

The information collected will be used only for research purposes and will be treated strictly confidential. If you have questions regarding this study, you may contact Zahra Zangenehmadar, at +1 514-848-2424, ext 7901.

Please provide the below information:

Name	
Name of organization	
Years of experience	
Email address	
Receive a copy of the findings	

Brief description about some of the parameters:

Pipe vintage: Particular time and place in which pipes are made
Pipe installation : Process of installation
Thrust restraint: Restraint to bear longitudinal stresses
Dissimilar metals: connection of two pipes with different materials
Disturbance: Changes in the support and loading structure on the pipe
Stray electrical currents: Occurrence of electrical currents between two objects that ideally should not have any.
Backflow potential: unwanted flow of water in the reverse direction
O&M practices: Quality of the performance of operation and maintenance practices.

Figure 4-9. Delphi questionnaire (continued)

1. With respect to **"Physical Factors"** how important is each criterion?

	Not at all Important	Unimportant	Neither Important nor Unimportant	Important	Extremely Important
Pipe material					
Pipe wall thickness					
Pipe age					
Pipe vintage*					
Pipe diameter					
Pipe lining and coating					
Pipe installation*					
Pipe manufacture					
Pipe lenght					
Pipe location					
Type of joints					
Thrust restraint*					
Dissimilar metals*					

2. With respect to **"Environmental Factors"**, how important is each criterion?

	Not at all Important	Unimportant	Neither Important nor Unimportant	Important	Extremely Important
Bedding soil type					
Backfill material					
Soil pH					
Groundwater					
Weather/Temperature					
Disturbance*					
Stray electrical currents*					
Seismic activity					
Traffic distribution/ land use					

3. With respect to **"Operational Factors",** how important is each criterion?

	Not at all Important	Unimportant	Neither Important nor Unimportant	Important	Extremely Important
Water pressure					
Water quality					
Water pH					
Water velocity					
Leakage					
Back-flow potential*					
O&M practices*					
Oxygen content					

Figure 4-10. Delphi questionnaire (continued)

4. If we had to limit the number of pipe failure factors from the previous list of physical, environmental and operational factors would you choose to keep? Please rank a minimum of 5 factors, starting from the most important.

Factor 1

Factor 2

Factor 3

Factor 4

Factor 5

Factor 6

Factor 7

Factor 8

Factor 9

Factor 10

5. Please list up to 5 factors from the previous list of physical, environmental and operational factors that you believe could be excluded from the pipe failure factors in water distribution networks.

Factor 1

Factor 2

Factor 3

Factor 4

Factor 5

6. If you have any further suggestions for **factors** affecting failure in water pipelines, that you believe could be important, please list below **the factors and the reasons** why they are important (optional).

Figure 4-11. Delphi questionnaire

Questionnaire 2

The questionnaire was released on June 2nd, 2014 and the collection duration lasted for 20 days. The questionnaire was designed in an online format on Qualtrics website which is a data collection platform. 38 questionnaires were sent out and collected from experts around the world to find the weight of importance of each factor in water pipeline deterioration. The years of experience and demographic distribution of these experts is summarized in

Figure 4-12 and Figure 4-13. In the five-question questionnaire, the experts are asked to identify the relative importance of each criterion in pipeline deterioration both separately and respect to others by using linguistic variables that will be discussed in Chapter 5.

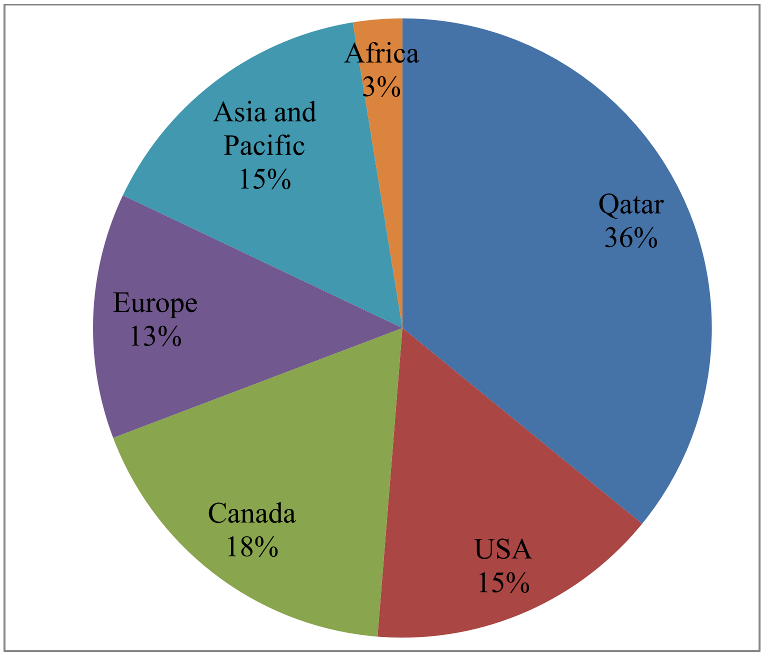


Figure 4-12.Demographic distribution of the experts

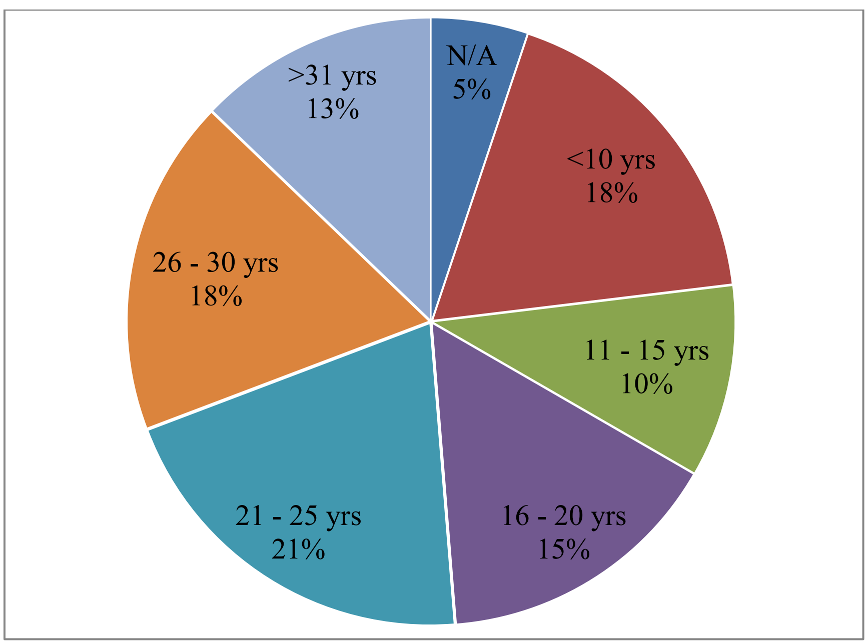


Figure 4-13.Years of experience of participants in the AHP and Entropy

The survey questionnaire

Informed Consent Form

This questionnaire aims at eliciting input on the factors that impact deterioration of water mains in distribution networks. The findings of this survey will be utilized in my PhD research on development of deterioration models for water distribution networks. It takes approximately 10 minutes to complete this questionnaire.

The factors are clustered in three groups; physical, environmental and operational. You are requested to rank these factors based on their relative importance in the first four questions. Sections 5 aims at ranking criteria from 1 to 10. If you would like to receive a copy of the findings of this questionnaire, please mark the appropriate box below.

The information collected will be used only for research purposes and will be treated strictly confidential. If you have questions regarding this study, you may contact Zahra Zangenehmadar, at +1 514-848-2424, ext 7901.

Please provide the below information:

Name	
Name of organization	
Years of experience	
Email address	
Receive a copy of the findings	

Brief Explanation about some of the factors:

Pipe installation: Process of installation
Dissimilar metals: connection of two pipes with different materials
Disturbance: Changes in the support and loading structure on the pipe
O&M practices: Quality of the performance of operation and maintenance practices

EL: Extremely Low - VL: Very Low - L: Low - M: Medium - H: High - VH: Very High - EH: Extremely High

Figure 4-14 AHP-Shannon questionnaire (continued)

1.Considering **"Deterioration"**, what is the relative importance of each category of factors listed on the left in comparison to the category listed on the right side? e.g. if physical factors on the right side has extremely high importance in comparison to Environmental factors on the left side, choose EH.

	EL	VL	L	M	H	VH	EH	
Physical Factors								Environmental Factors
Physical Factors								Operational Factors
Environmental Factors								Operational Factors

2.Considering **"Physical Factors"**, what is the relative importance of each criterion listed on the left in comparison to the criterion listed on the right side? you could compare them as explained in Question 1.

	EL	VL	L	M	H	VH	EH	
Pipe material								Pipe installation
Pipe material								Pipe age
Pipe material								Pipe lining and coating
Pipe material								Pipe wall thickness
Pipe material								Dissimilar metals
Pipe material								Type of joints
Pipe installation								Pipe age
Pipe installation								Pipe lining and coating
Pipe installation								Pipe wall thickness
Pipe installation								Dissimilar metals
Pipe installation								Type of joints
Pipe age								Pipe lining and coating
Pipe age								Pipe wall thickness
Pipe age								Dissimilar metals
Pipe age								Type of joints
Pipe lining and coating								Pipe wall thickness
Pipe lining and coating								Dissimilar metals
Pipe lining and coating								Type of joints
Pipe wall thickness								Dissimilar metals
Pipe wall thickness								Type of joints
Dissimilar metals								Type of joints

Figure 4-15. AHP-Shannon questionnaire (continued)

3.Considering **"Environmental Factors"**, what is the relative importance of each criterion listed on the left in comparison to the criterion listed on the right side? you could compare them as explained in Question 1.

	EL	VL	L	M	H	VH	EH	
Bedding soil type	○	○	○	○	○	○	○	Backfill material
Bedding soil type	○	○	○	○	○	○	○	Soil pH
Bedding soil type	○	○	○	○	○	○	○	Seismic activity
Bedding soil type	○	○	○	○	○	○	○	Disturbance
Backfill material	○	○	○	○	○	○	○	Soil pH
Backfill material	○	○	○	○	○	○	○	Seismic activity
Backfill material	○	○	○	○	○	○	○	Disturbance
Soil pH	○	○	○	○	○	○	○	Seismic activity
Soil pH	○	○	○	○	○	○	○	Disturbance
Seismic activity	○	○	○	○	○	○	○	Disturbance

4.Considering **"Operational Factors"**, what is the relative importance of each criterion listed on the left in comparison to the criterion listed on the right side? you could compare them as explained in Question 1.

	VL	L	ML	M	MH	H	VH	
Water pressure	○	○	○	○	○	○	○	O&M practices
Water pressure	○	○	○	○	○	○	○	Leakage
Water pressure	○	○	○	○	○	○	○	Water pH
O&M practices	○	○	○	○	○	○	○	Leakage
O&M practices	○	○	○	○	○	○	○	Water pH
Leakage	○	○	○	○	○	○	○	Water pH

5.What is the relative importance of each of the following criteria? e.g. if pipe material is most important factor in deterioration, put 10 and if water pressure is the least important factor, put 1.

	1-10 (Integer)
Pipe material	
Pipe installation	
Pipe age	
Pipe lining and coating	
Pipe wall thickness	

Figure 4-16. AHP-Shannon questionnaire (continued)

Dissimilar metals	
Type of joints	
Bedding soil type	
Backfill material	
Soil pH	
Seismic activity	
Disturbance	
Water pressure	
O&M practices	
Leakage	
Water pH	

6. If you have any further suggestions for **factors** affecting failure in water pipelines, that you believe could be important, please list below **the factors and the reasons** why they are important (optional).

Figure 4-17. AHP-Shannon questionnaire

CHAPTER 5: MODEL DEVELOPMENT AND IMPLEMENTATION

5.1. Chapter Overview

This chapter is started with an introduction to the condition model (section 5.2). It starts with Delphi survey and the findings through questionnaires are discussed. Then, the results of FAHP-Shannon Entropy questionnaires are applied to develop the condition index equation for predicting the condition of the pipe segments. Section 5.3 is about the model which predicts remaining useful life based on condition, breakage rate and other physical properties of the pipeline utilizing artificial neural network. The model is trained, tested and validated through data of city of Montréal. The remaining useful life, the breakage rate and the associated cost of replacement or rehabilitation of each pipeline are applied in budget allocation model described in section 5.4 to find the best optimized maintenance scheduling of the pipelines by the aid of Genetic Algorithm. Afterwards, new two-tier inspection planning model which has covered limitation of one technique with benefits of the other method is explained in section 5.5. All the models are implemented to the case study of historical data related to the municipality of Montreal water distribution network in section 5.6.

5.2. Condition Model

5.1.1. **Delphi study**

The applied methodology to develop the condition model is discussed in detail in section 3.3. In this section the process of model implementation and development will be discussed. In the first step, the Delphi study is used to identify the most important factors in literature. This survey is performed by spreading questionnaires (4.2.3) in three consecutive rounds asking the experts to give their ideas. The respondents received feedback from their responses in each round. The collected responses from experts on the first and second rounds are shown in Figure 5-1 and Figure 5-2.

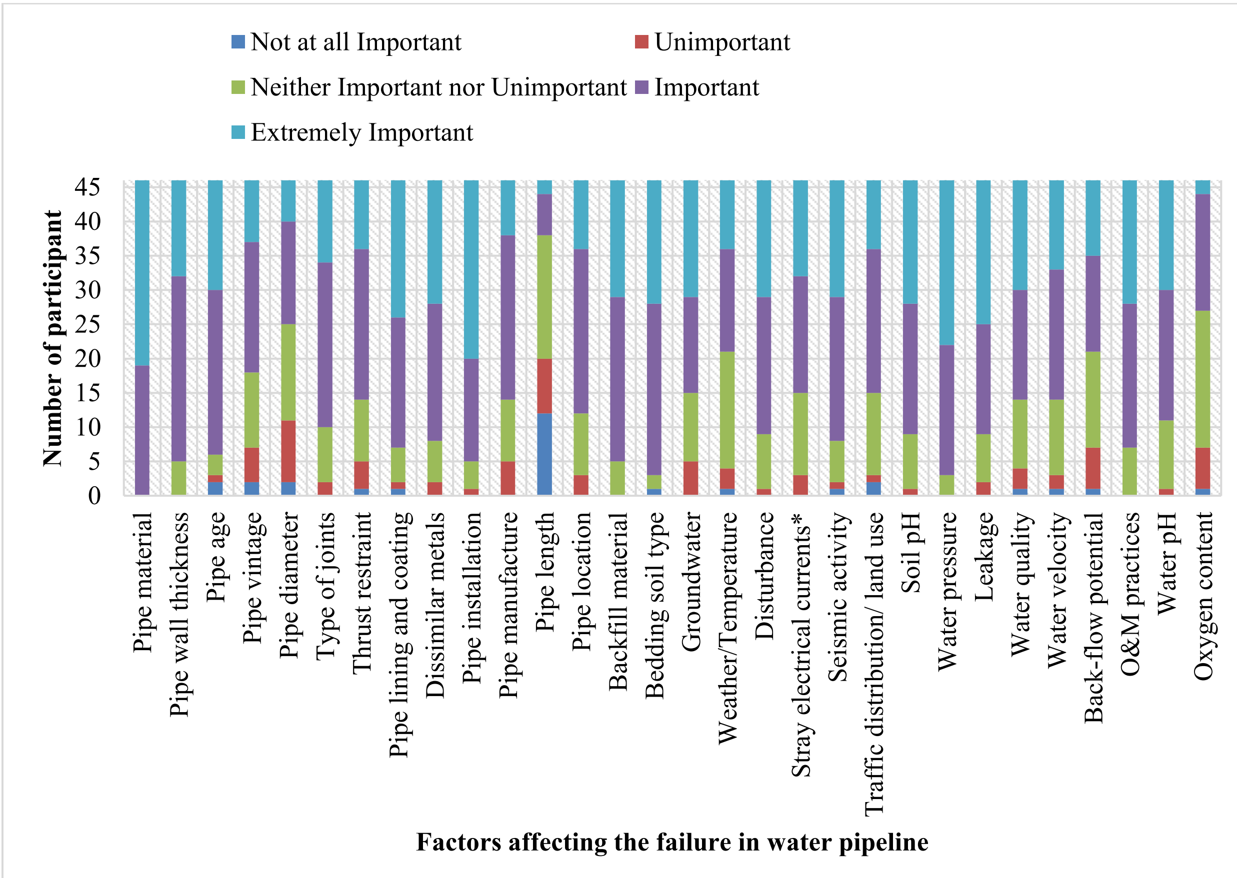


Figure 5-1.Collected responses from experts for Importance of factors (1st round)

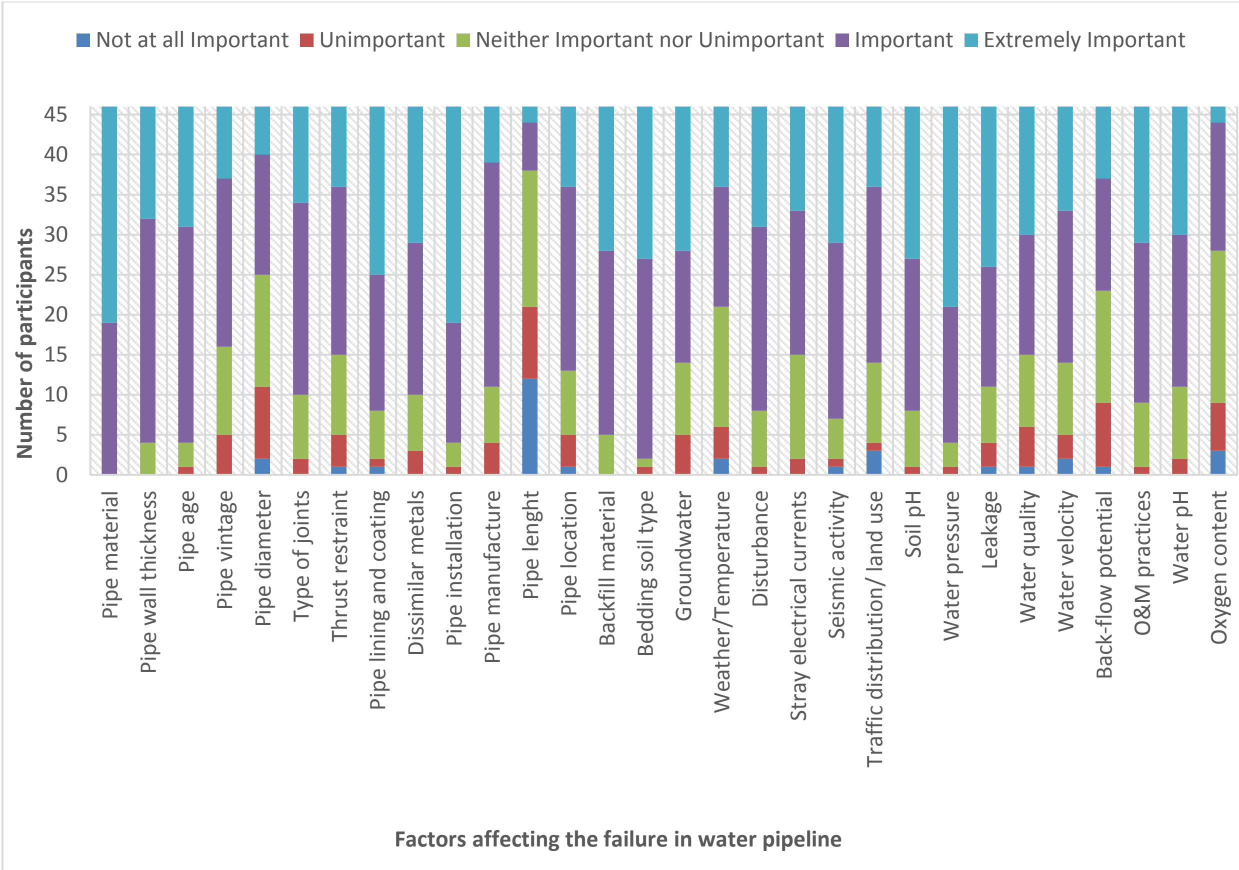


Figure 5-2.Collected responses from experts for Importance of factors (2nd round)

The average score of each parameter in these figures is calculated by assigning values to the available options in questions 1 to 3. As a way of illustration, following values are assigned to the options in the questionnaire; 1 to not at all important, 2 to unimportant, 3 to neither important nor unimportant, 4 to important, and 5 to extremely important. In the second round, the same questionnaires were sent to the previous experts along with the average answers of first round to provide them with feedback and ask them to revise their responses if necessary. The new results were collected and tabulated exactly same as previous round and the process continued for the third round. Since none of the experts wished to change his opinion, the Delphi survey was terminated at third round. Summary of the average data collected from first to third rounds, the differences between the results in each two consecutive round and the final score are shown in Table 5-1.

Table 5-1.Average score for 1st, 2nd and 3rd round and the differences

	Factors	1st round	2nd round	3rd round	Difference 1st - 2nd	Difference 2nd - 3rd	Final score
1	Pipe material	4.59	4.59	4.59	0	0	4.59
2	Pipe wall thickness	4.2	4.22	4.22	0.02	0	4.22
3	Pipe age	4.11	4.22	4.22	0.11	0	4.22
4	Pipe vintage	3.63	3.74	3.74	0.11	0	3.74
5	Pipe diameter	3.3	3.28	3.28	0.02	0	3.28
6	Type of joints	4	4	4	0	0	4
7	Thrust restraint	3.76	3.76	3.76	0	0	3.76
8	Pipe lining and coating	4.22	4.24	4.24	0.02	0	4.24
9	Dissimilar metals	4.13	4.09	4.09	0.04	0	4.09
10	Pipe installation	4.46	4.48	4.48	0.02	0	4.48
11	Pipe manufacture	3.8	3.83	3.83	0.02	0	3.83
12	Pipe length	2.52	2.5	2.5	0.02	0	2.5
13	Pipe location	3.85	3.8	3.8	0.04	0	3.8
14	Backfill material	4.28	4.28	4.28	0	0	4.28
15	Bedding soil type	4.33	4.33	4.33	0	0	4.33
16	Groundwater	3.98	3.98	3.98	0	0	3.98
17	Weather/Temperature	3.63	3.59	3.59	0.04	0	3.59
18	Disturbance	4.15	4.13	4.13	0.02	0	4.13
19	Stray electrical currents	3.91	3.91	3.91	0	0	3.91
20	Seismic activity	4.13	4.15	4.15	0.02	0	4.15
21	Traffic distribution/ Landuse	3.8	3.76	3.76	0.04	0	3.76
22	Soil pH	4.2	4.22	4.22	0.02	0	4.22
23	Water pressure	4.48	4.43	4.43	0.04	0	4.43
24	Leakage	4.17	4.11	4.11	0.07	0	4.11
25	Water quality	3.89	3.87	3.87	0.02	0	3.87
26	Water velocity	3.85	3.83	3.83	0.02	0	3.83
27	Back-flow potential	3.57	3.48	3.48	0.09	0	3.48
28	O&M practices	4.22	4.15	4.15	0.07	0	4.15
29	Water pH	4.11	4.07	4.07	0.04	0	4.07
30	Oxygen content	3.22	3.17	3.17	0.04	0	3.17

As can be seen, the differences between first two rounds are less than 0.2 in all the factors and there is no difference between 2nd and 3rd rounds. Therefore, it could be concluded that the experts have reached consensus. Considering the final scores, those factors with average value equal and more than 4 were chosen for further analysis since 4 was considered as important in designing the questionnaire.

Question 4 seeks to limit the number of factors to ten asking experts to prioritize factors based on their importance. On the contrary, question 5 asks the participants to eliminate five least important factors in failure of water pipelines. Experts were requested to challenge the questions and suggested factors through question 6.

Table 5-2.Selected factors from questionnaires

	Factors selected in the questions 1 to 3	Factors selected in question 4	Factors excluded in question 5
1	Pipe material	Pipe material	Pipe length
2	Pipe installation	Pipe age	Pipe diameter
3	Water pressure	Pipe installation	Backflow potential
4	Bedding soil type	Pipe lining and coating	Pipe manufacture
5	Backfill material	Bedding soil type	Weather/temperature
6	Pipe lining and coating	Pipe wall thickness	
7	Pipe wall thickness	Water pressure	
8	Pipe age	Type of joints	
9	Soil pH	Disturbance	
10	Seismic activity	O&M practices	
11	O&M practices		
12	Disturbance		
13	Leakage		
14	Dissimilar metals		
15	Water pH		
16	Type of joints		

The last 3 questions were designed to validate the results of the first 3 questions. The chosen factors were ranked and the first ten factors were selected to compare with the factors chosen in the first three questions. The factors selected previously and in the fourth question are summarized in Table 5-2. Comparing selected factors in both questions, all the ten factors of question four were selected during questions one to three and all the five selected factors of question five were not selected in questions one to three. This validates the results of the Delphi study since it shows that the results are the same when the study is conducted in another way.

The internal consistency was checked for continuous rounds of Delphi and Cronbach's Alpha were calculated. The Alpha is equal to 0.919 for 46 questionnaires of the first round. It is also calculated as 0.923 for the same number of questionnaires at the second round. Since the Cronbach's Alpha is greater than 0.9 in both rounds, the survey has high reliability.

Table 5-3. Reliability Statistics

Number of Items	Cronbach's Alpha (1st round)	Cronbach's Alpha (2nd round)
46	0.919	0.923

5.1.2. **FAHP-Shannon Entropy Survey**

After running the Delphi survey, another survey is conducted to calculate the weight of importance for each of the selected factors in Delphi study. In the primary question, the experts were asked to identify the importance of classes of factors in pipeline deterioration by using linguistic variables of Table 5-4.

Table 5-4.Linguistic variables for the importance weight of each criterion (Chen, 2000)

Linguistic Term	**Fuzzy triangular Number**
Extremely Low (EL)	(0.0, 0.0, 0.1)
Very Low (VL)	(0.0, 0.1, 0.3)
Medium Low (ML)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
Medium High (MH)	(0.5, 0.7, 0.9)
Very High (VH)	(0.7, 0.9, 1.0)
Extremely High (EH)	(0.9, 1.0, 1.0)

After data collection is completed, the responses are fuzzified and averaged. The average of the responses collected for question 1 is summarized in Table 5-5. As can be seen, physical factors have the highest effect in deterioration of the water pipeline. Operational and Environmental factors are ranked as second and third important categories in pipeline deterioration.

Table 5-5.Pairwise comparison matrix for Physical, Environmental and Operational factors

	Physical Factors	Environmental Factors	Operational Factors
Physical Factors	(1, 1, 1)	(0.60, 0.78, 0.92)	(0.29, 0.44, 0.60)
Environmental Factors	(0.08, 0.21, 0.40)	(1, 1, 1)	(0.47, 0.64, 0.78)
Operational Factors	(0.40, 0.56, 0.71)	(0.22, 0.36, 0.53)	(1, 1, 1)

In the subsequent questions, the importance of factor in each category was questioned. The experts were asked to identify the relative importance of factors in operational, environmental and physical classes. It can be seen that water pressure and O&M practices are the operational parameters that affect the deterioration of water pipelines at most. In category of Environmental factors, bedding soil type, seismic activity and backfill material are the most important factors in deterioration of water pipelines respectively. Pipe material, pipe installation and pipe age are the first three significant factors in physical factors.

Table 5-6.Pairwise comparison for Operational factors

	Water pressure	O&M practices	Leakage	Water pH
Water pressure	(1, 1, 1)	(0.67, 0.82, 0.90)	(0.67, 0.83, 0.91)	(0.38, 0.53, 0.67)
O&M practices	(0.10, 0.18, 0.33)	(1, 1, 1)	(0.54, 0.72, 0.85)	(0.41, 0.56, 0.71)
Leakage	(0.10, 0.17, 0.33)	(0.15, 0.28, 0.46)	(1, 1, 1)	(0.38, 0.53, 0.67)
Water pH	(0.33, 0.47, 0.62)	(0.29, 0.44. 0.59)	(0.33, 0.47, 0.62)	(1, 1, 1)

Table 5-7.Pairwise comparison for Environmental factors

	Bedding soil type	Backfill material	Soil pH	Seismic activity	Disturbance
Bedding soil type	(1, 1, 1)	(0.56, 0.73, 0.85)	(0.44, 0.62, 0.78)	(0.38, 0.56, 0.73)	(0.5, 0.67, 0.82)
Backfill material	(0.14, 0.26, 0.43)	(1, 1, 1)	(0.42, 0.62, 0.78)	(0.26, 0.42, 0.6)	(0.39, 0.57, 0.72)
Soil pH	(o.21, 0.37, 0.55)	(0.21, 0.37, 0.57)	(1, 1, 1)	(0.17, 0.32, 0.51)	(0.20, 0.35, 0.53)
Seismic activity	(0.26, 0.43, 0.61)	(0.4, 0.57, 0.73)	(0.48, 0.67, 0.82)	(1, 1, 1)	(0.52, 0.70, 0.84)
Disturbance	(0.17, 0.32, 0.5)	(0.27, 0.42, 0.60)	(0.46, 0.64, 0.79)	(0.15, 0.29, 0.47)	(1, 1, 1)

Table 5-8.Pairwise comparison for Physical factors

	Pipe material	Pipe installation	Pipe age	Pipe lining and coating	Pipe wall thickness	Dissimilar metals	Type of joints
Pipe material	(1, 1, 1)	(0.50, 0.68, 0.82)	(0.46, 0.63, 0.76)	(0.42, 0.61, 0.78)	(0.46, 0.65, 0.81)	(0.42, 0.56, 0.70)	(0.46, 0.65, 0.81)
Pipe installation	(0.17, 0.31, 0.49)	(1, 1, 1)	(0.36, 0.52, 0.68)	(0.37, 0.56, 0.73)	(0.34, 0.52, 0.68)	(0.37, 0.54, 0.71)	(0.35, 0.53, 0.71)
Pipe age	(0.22, 0.36, 0.53)	(0.31, 0.47, 0.63)	(1, 1, 1)	(0.40, 0.59, 0.76)	(0.36, 0.54, 0.72)	(0.36, 0.53, 0.70)	(0.36, 0.54, 0.73)
Pipe lining and coating	(0.22, 0.38, 0.57)	(0.26, 0.43, 0.62)	(0.23, 0.40, 0.59)	(1, 1, 1)	(0.36, 0.54, 0.71)	(0.39, 0.55, 0.71)	(0.31, 0.48, 0.66)
Pipe wall thickness	(0.18, 0.34, 0.53)	(0.31, 0.48, 0.65)	(0.28, 0.46, 0.64)	(0.28, 0.46, 0.63)	(1, 1, 1)	(0.32, 0.50, 0.67)	(0.25, 0.42, 0.61)
Dissimilar metals	(0.29, 0.43, 0.58)	(0.28, 0.45, 0.62)	(0.29, 0.46, 0.64)	(0.28, 0.44, 0.60)	(0.32, 0.49, 0.67)	(1, 1, 1)	(0.34, 0.50, 0.67)
Type of joints	(0.18, 0.34, 0.53)	(0.28, 0.46, 0.64)	(0.26, 0.45, 0.64)	(0.34, 0.51, 0.68)	(0.38, 0.57, 0.74)	(0.32, 0.49, 0.66)	(1, 1, 1)

The global weight is computed from solving matrices of Table 5-5 and extracting the weights. The local weight of importance is calculated from Tables 5-6 to 5-8 which display the pairwise comparison matrices for operational, environmental and physical factors. This global weight of importance for each category is multiplied by the local weight of importance of each sub-category to find the total weight of importance for each factor. It can be seen that criteria of pipe material, water pressure, pipe installation, pipe age and types of joints are the most important factors in pipeline deterioration in water infrastructure which has been determined by FAHP method.

Table 5-9.Total weights of importance for all parameters

	Global weights		Local weights	Weights of importance
Physical	0.369129	Pipe material	0.178801	0.085314
		Pipe installation	0.149646	0.071402
		Pipe age	0.146582	0.069940
		Pipe lining and coating	0.135983	0.064883
		Pipe wall thickness	0.130229	0.062138
		Dissimilar metals	0.132782	0.063356
		Type of joints	0.125644	0.059950
Environmental	0.309955	Bedding soil type	0.233744	0.066893
		Backfill material	0.198028	0.056672
		Soil pH	0.164687	0.047130
		Seismic activity	0.220882	0.063212
		Disturbance	0.182371	0.052191
Operational	0.320865	Water pressure	0.313768	0.074364
		O&M practices	0.246516	0.058425
		Leakage	0.201185	0.047681
		Water pH	0.238179	0.056449

To check the reliability of the questionnaires and responses, consistency index (CI) and consistency ratio (CR) were checked for all of the pairwise comparison matrices and results are summarized in Table 5-10.

Table 5-10.Consistency in pairwise matrices

Pairwise comparison Matrix	CI	CR
Q1	0.1059	0.1827
Q2	0.1077	0.1197
Q3	0.1068	0.0809
Q4	0.1090	0.0973

The consistency index should be less than 10% to have a consistent survey. As can be seen CI is less than 10% for all the four questions. The previous built pairwise comparison matrix for FAHP was used this time to perform Shannon Entropy calculations. Based on the steps in section 3.3.2, normalizations were performed in the beginning and entropy was calculated from equation 3-13. Afterwards, the degree of diversification and weight of importance were computed based on the calculated amount of entropy. The entropy, degree of diversification and weight of importance of the deterioration factors were shown in Table 5-11.

Table 5-11.Entropy, degree of diversification and weight of importance of the factors

Criteria/ Responses	e_j	d_j	w_j
Pipe material	0.43974	0.56026	0.066174
Pipe installation	0.53391	0.46609	0.080345
Pipe age	0.53840	0.46160	0.081019
Pipe lining and coating	0.56588	0.43412	0.085155
Pipe wall thickness	0.58516	0.41484	0.088057
Dissimilar metals	0.58820	0.41180	0.088515
Type of joints	0.59528	0.40472	0.089579
Bedding soil type	0.31559	0.68441	0.047492
Backfill material	0.36496	0.63504	0.054921
Soil pH	0.40421	0.59579	0.060827
Seismic activity	0.34103	0.65897	0.051320
Disturbance	0.38311	0.61689	0.057651

Water pressure	0.18103	0.81897	0.027242
O&M practices	0.23985	0.76015	0.036094
Leakage	0.27448	0.72552	0.041305
Water pH	0.29442	0.70558	0.044306

e_j = entropy

d_j = degree of diversification

w_j = weight of importance

The final weight will be an integration of both Entropy and FAHP methods since Entropy measures the objective weights while FAHP calculate the subjective weights. This integration was performed to consider both subjective and objective weights. Equation 3-14 is used to find the weights of importance of the parameters.

Table 5-12.Weights of deterioration factors from Entropy and FAHP

Criterion	Abbreviation	Weights of importance
Pipe installation	I	0.09101
Pipe age	A	0.08989
Pipe material	M	0.08956
Dissimilar metals	DM	0.08896
Pipe lining and coating	LC	0.08765
Pipe wall thickness	T	0.08680
Type of joints	J	0.08519
Seismic activity	SA	0.05146
Bedding soil type	ST	0.05040
Backfill material	BM	0.04937
Disturbance	DI	0.04773
Soil pH	SP	0.04548
Water pH	WP	0.03967
O&M practices	O	0.03345
Water pressure	P	0.03214
Leakage	LE	0.03124

The weights of importance from FAHP, Entropy method and integration of both methods are calculated and illustrated in Figure 5-3. The factors are organized based on their weights from the integration of both methods. It can be seen that the prediction of weight of importance for most of the criteria such as leakage, backfill material, pipe age, pipe material are approximately the same in all of the 3 methods and the differences are less than 2%. Greater differences are detected in water pressure, type pf joints, dissimilar metals and pipe wall thickness respectively. This confirms that the computed weight of importance for each of the criterion is calculated correctly. Moreover, more researches and clarifications should be performed to identify the effects of these criteria precisely.

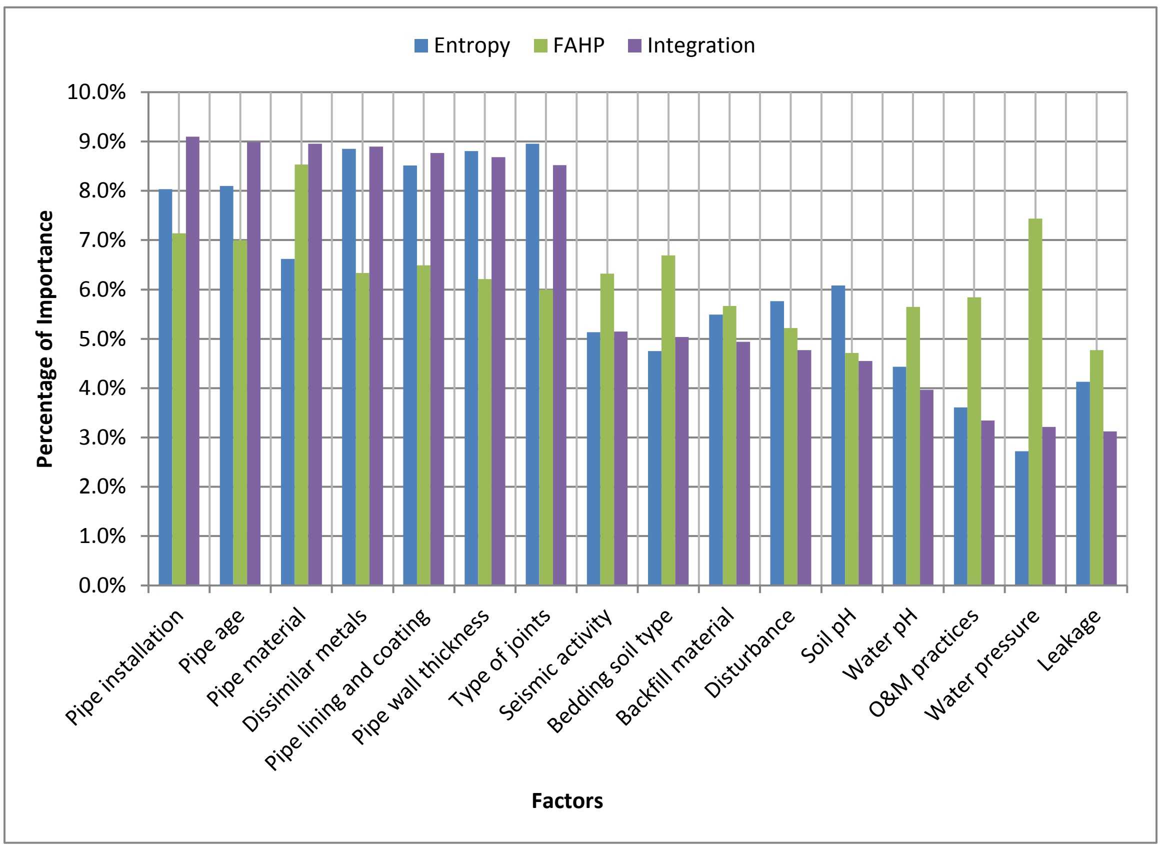


Figure 5-3.Comparison of weights from different methods

5.1.3. **Condition Index**

The important parameters affected the deterioration are figured out in section 5.1.1.5.1.2 Besides, their respective weights of importance are calculated in section 5.1.2. The findings of these two sections will be used to implement the condition index. The condition index is basically calculated from equation 3-15. However, after finding the W_i, the equation will become as:

$$Condition\ Index = \sum_{i=1}^{n} EA_i W_i \tag{5-1}$$

$$= 0.1255 \times A + 0.1250 \times M + 0.1212 \times T + 0.1270 \times I + 0.1224 \times LC + 0.0718 \times SA + 0.0704 \times ST + 0.0689 \times BM + 0.1242 \times DI + 0.0436 \times LE$$

The EA_i are extracted from classification tables (Table 3-3 to Table 3-12) in Chapter 3. The weight of each factor shows its importance in deterioration of pipelines and consequently in its condition. After that, the conditions of pipelines are calculated based on the developed condition index model and pipes are classified from critical to excellent based on Numeric scale and criteria in Table 5-13 which shows the condition of the pipe. The condition rating scale proposed by Al-Barqawi (2006) is utilized in this research to find the classes of pipeline condition.

Table 5-13.Numeric and Linguistic Scales for condition rating of water mains (adopted from Al-Barqawi, 2006)

Numeric Scale	Linguistic Scale	Criteria	Action
0 – 1	Excellent	Newly/recently installed	No action required
1 – 2	Very Good	Like new with no sign of corrosion or deterioration pipe wall thickness. BR≤0.05	Re-assess in 15 years
2 – 4	Good	Coating, lining still intact. Remaining wall thickness more than 90% of original	Re-assess in 10 years. Schedule for Cathodic protection within next 10 years
4 – 6	Moderate	Some damage to coating and/or lining noted. Remaining wall thickness 75% or more of original	Re-assess in 5 years. Schedule for lining and rehabilitation within the next 10 years
6 – 7	Poor	No lining or coating. Significant signs of internal or external corrosion. Remaining wall thickness 50 to 75% of original	Schedule for rehabilitation or replacement within the next 5 years
7 – 10	critical	Severe internal or external corrosion. Remaining wall thickness less than 50% of original. BR≥3	Immediate repair or replacement required

BR= breakage rate (breaks/km/year)

The condition model is applied to the case study of city of Montréal and the condition of each pipe segment has been calculated. Detailed results are displayed in section 5.6 which talks about implementing model to the case study of the city of Montréal..

5.3. Remaining Useful Life Model

As described in research methodology, artificial neural network (ANN) is used to estimate expected remaining useful life of the pipelines. Furthermore, generalized regression neural network (GRNN) is also applied to approximate the function that can be used estimating remaining useful life. Different number of neurons, hidden layers and training algorithm were used to find the best model for predicting the residual useful life.

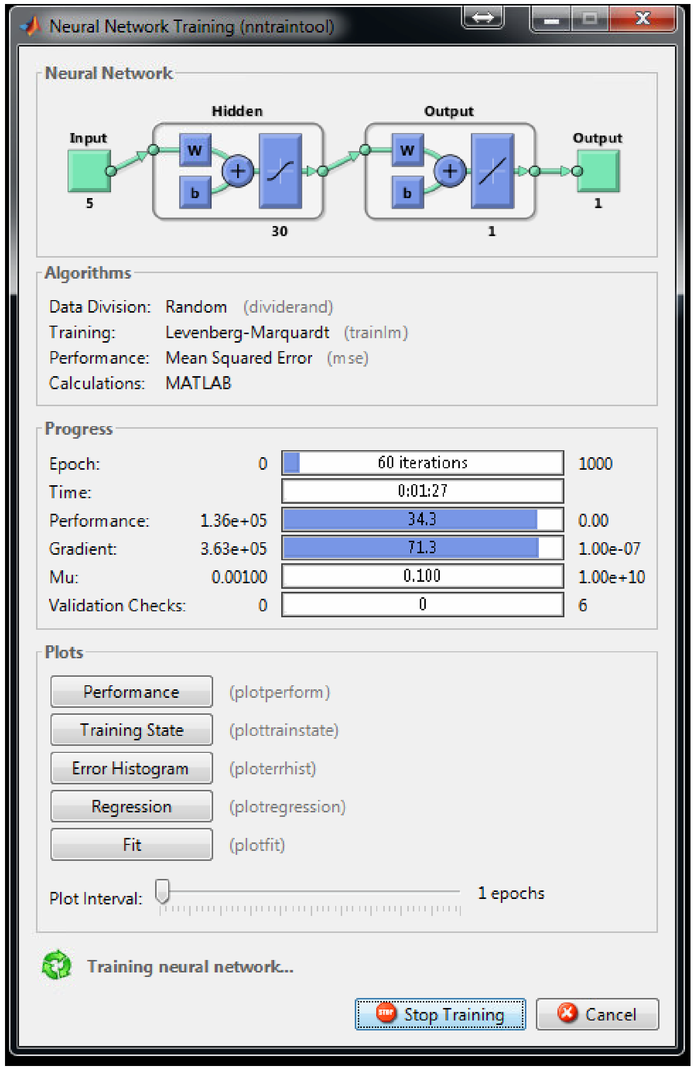


Figure 5-4.Sample structure of neural Network in Matlab

The number of hidden layers varies between 1 and 2 and models are trained by 10, 15, 20, 25, 30, 35, and 40 neurons. Also three algorithms of Levenberg–Marquardt (LM), Bayesian Regularization (BR) and Scaled Conjugate Gradient (SCG) were used for training the data. Considering the differences in training algorithm, neuron and hidden layer, 42 different models were developed and their results were compared. Figure 5-5 to Figure 5-7 display effects of number of neurons on coefficient of determination.

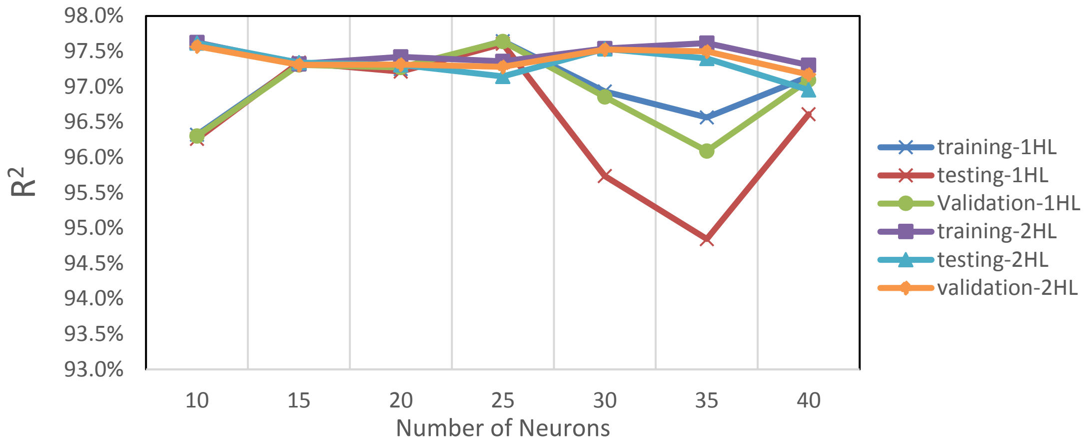


Figure 5-5. R^2 values of ANN models using LM algorithm

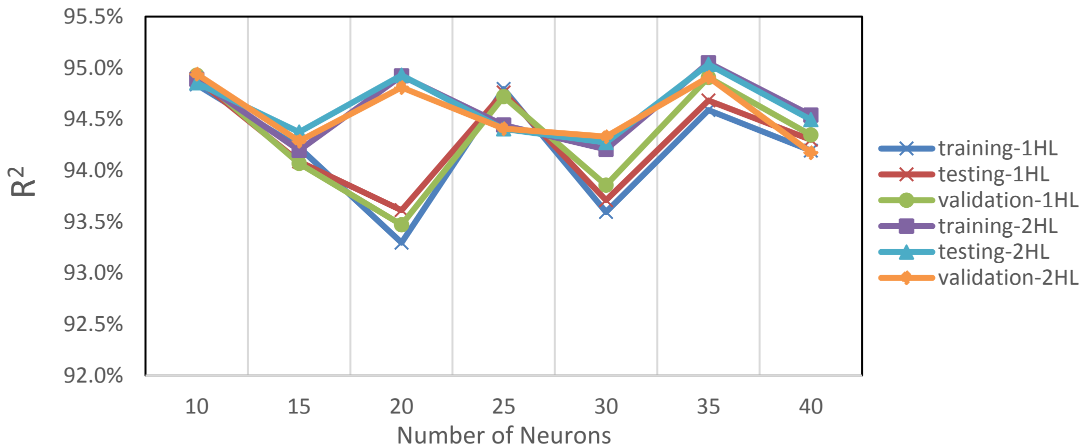


Figure 5-6. R^2 values of ANN models using SCG algorithm

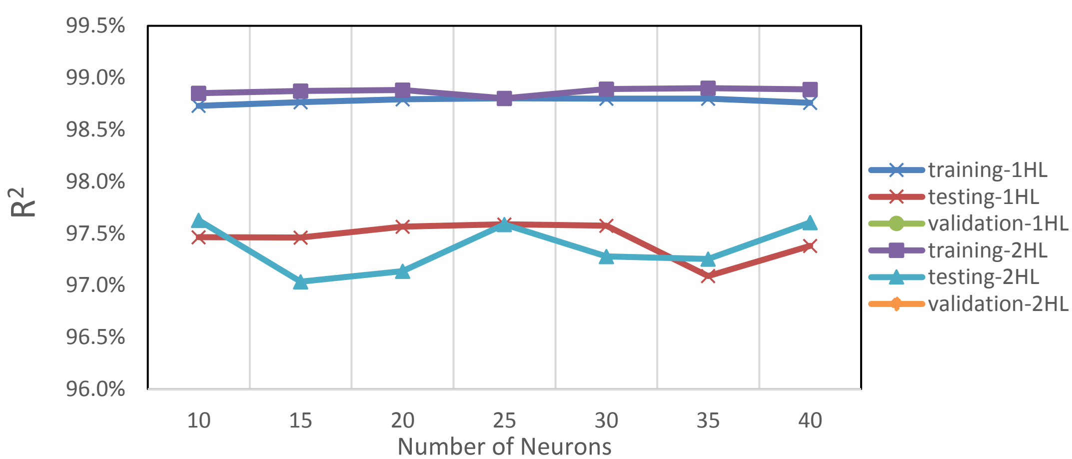


Figure 5-7. R^2 values of ANN models using BR algorithm

Also Figure 5-8, Figure 5-9, Figure 5-10, and Figure 5-11 show the change of MAE, RAE, MAPE, and RRSE in comparison to number of neurons respectively. Increasing the number of hidden layers results in better performance and takes more time, however it doesn't alter the accuracy in a great deal in this case. This can be seen from Figure 5-8 to Figure 5-11 which display that the number of neurons does not affect the accuracy a lot.

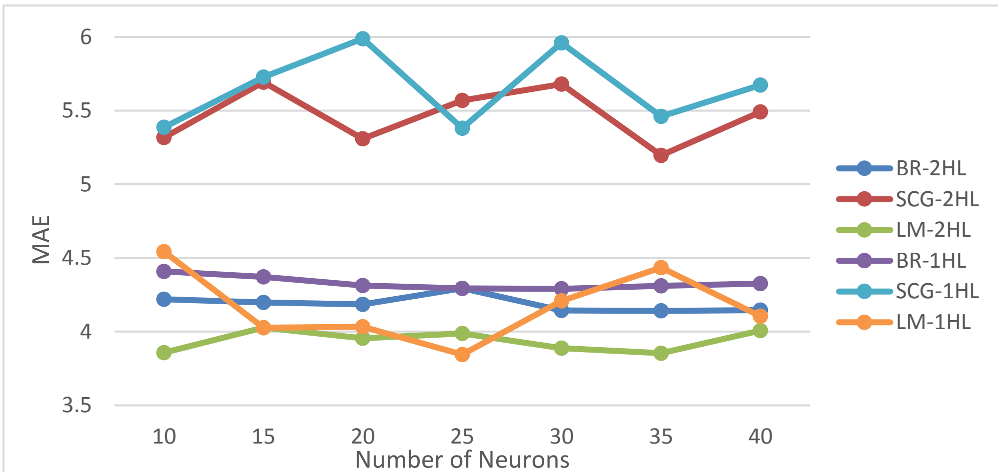


Figure 5-8. MAE values of ANN models

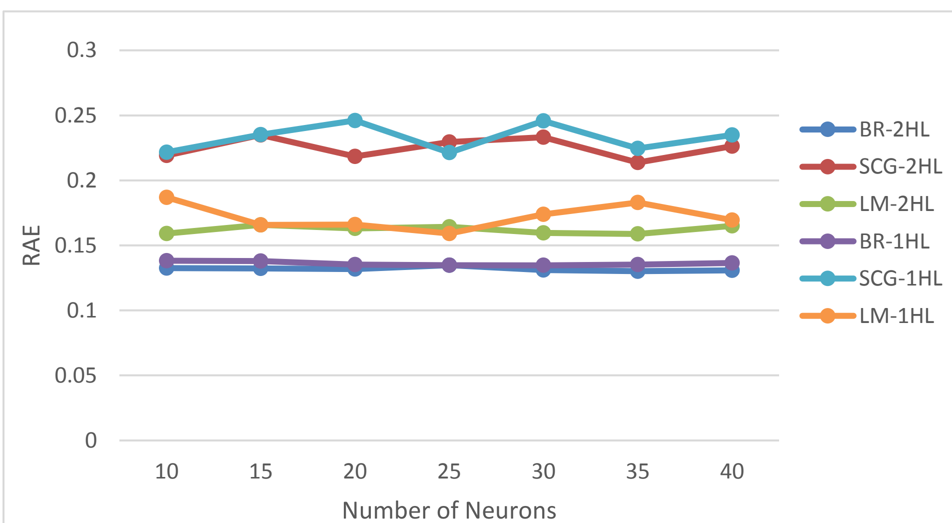


Figure 5-9.RAE values of ANN models

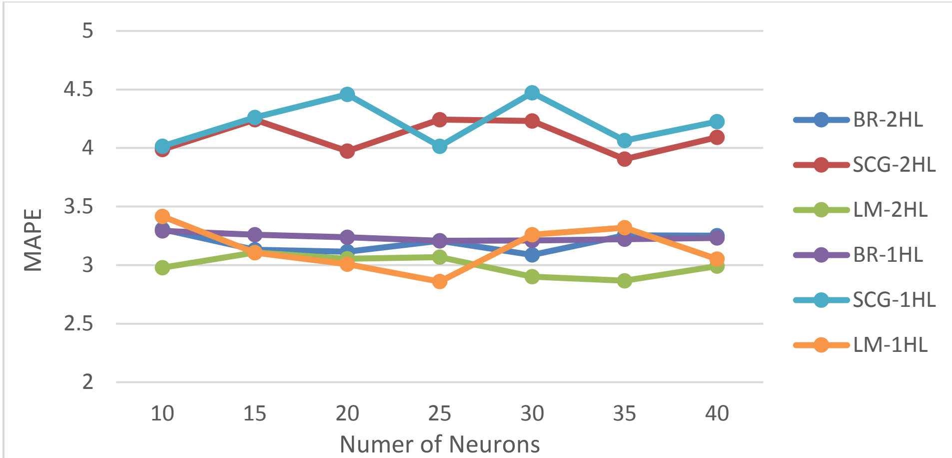


Figure 5-10.MAPE values of ANN models

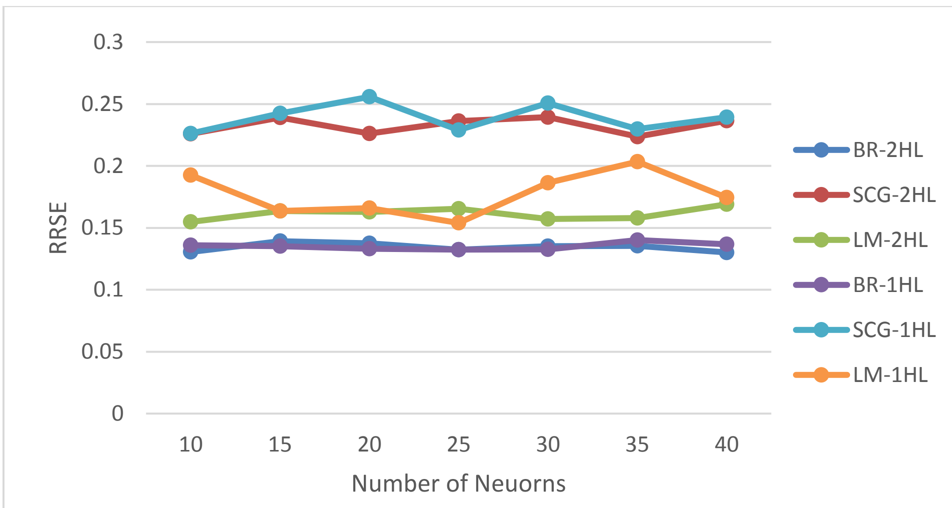


Figure 5-11. RRSE values of ANN models

It can be seen that the Levenberg-Marquardt algorithm will have the fastest convergence because this problem is a function approximation type. Levenberg-Marquardt method is used whenever an accurate training is required. In many cases, Levenberg-Marquardt algorithm can obtain lower mean square errors in comparison to other algorithms tested. The storage requirements of Levenberg-Marquardt algorithm are larger than the other algorithms tested.

The performance of the models was assessed based on R^2, mean absolute error (MAE), relative absolute error (RAE), root relative square error (RRSE) and mean absolute percentage error (MAPE) and the amounts of each error index are shown in Table 5-14 for one hidden layer and Table 5-15 for two hidden layers. 5 mentioned performance indices are calculated for 3 different algorithms of BR, LM and SCG and 8 different neuron number of 10, 15, 20, …and 40. It could be observed that there is no performance index available in validation phase when data are trained by Bayesian Regularization algorithm because Bayesian regularization algorithm does not validate data. It only trains and tests the data.

As can be seen from comparisons of models in Table 5-14 and Table 5-15, the final model will be the one with 1 hidden layer and 25 neurons which shows highest accuracy for predicting the remaining useful life. The value of performance indices of RAE, MAE, R^2, RRSE and MAPE are 0.159, 3.844, 0.976, 0.153 and 2.86 respectively. Therefore, this model will be applied to the case study of the city of Montreal. This model will be considered as high accuracy forecast model since MAPE is less than 10% and the amounts of RAE and RRSE are very small. Furthermore, in this case mean absolute error (MAE) is 3.8 which is reasonably good in comparison to the ultimate age considered for the pipelines in this case.

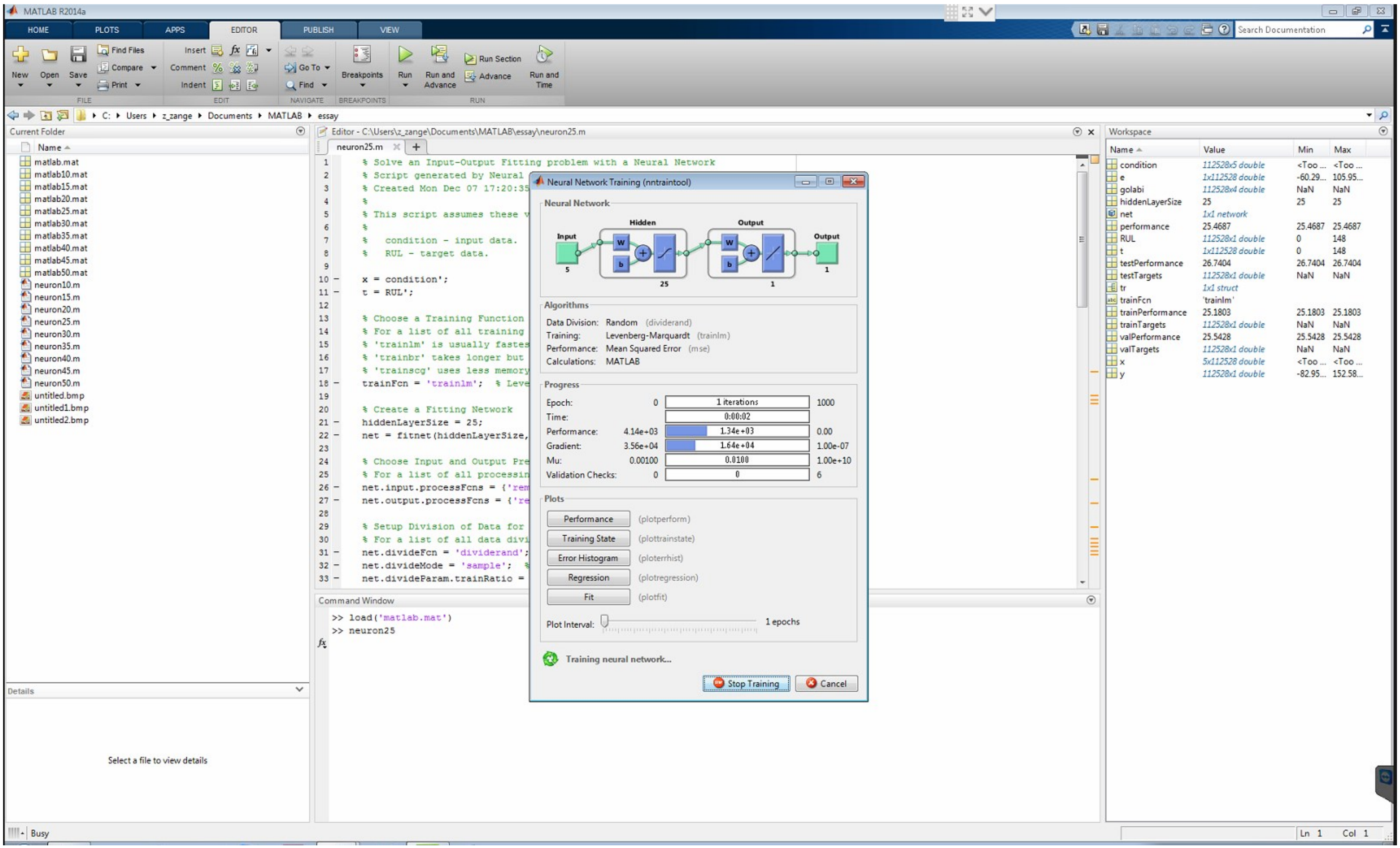

MATLAB R2014a
HOME
PLOTS
APPS
EDITOR
PUBLISH
VIEW
Search Documentation
New
Open
Save
Find Files
Compare
Print
Insert
Comment
Indent
Go To
Find
Breakpoints
Run
Run and Advance
Run Section
Advance
Run and Time
FILE
EDIT
NAVIGATE
BREAKPOINTS
RUN
C: ▸ Users ▸ z_zange ▸ Documents ▸ MATLAB ▸ essay
Current Folder
Name
matlab.mat
matlab10.mat
matlab15.mat
matlab20.mat
matlab25.mat
matlab30.mat
matlab35.mat
matlab40.mat
matlab45.mat
matlab50.mat
neuron10.m
neuron15.m
neuron20.m
neuron25.m
neuron30.m
neuron35.m
neuron40.m
neuron45.m
neuron50.m
untitled.bmp
untitled1.bmp
untitled2.bmp
Details
Select a file to view details
Editor - C:\Users\z_zange\Documents\MATLAB\essay\neuron25.m
neuron25.m
% Solve an Input-Output Fitting problem with a Neural Network
% Script generated by Neural
% Created Mon Dec 07 17:20:35
% This script assumes these v
% condition - input data.
% RUL - target data.
x = condition';
t = RUL';
% Choose a Training Function
% For a list of all training
% 'trainlm' is usually fastes
% 'trainbr' takes longer but
% 'trainscg' uses less memory
trainFcn = 'trainlm'; % Leve
% Create a Fitting Network
hiddenLayerSize = 25;
net = fitnet(hiddenLayerSize,
% Choose Input and Output Pre
% For a list of all processin
net.input.processFcns = {'rem
net.output.processFcns = {'re
% Setup Division of Data for
% For a list of all data divi
net.divideFcn = 'dividerand';
net.divideMode = 'sample'; %
net.divideParam.trainRatio =
Command Window
>> load('matlab.mat')
>> neuron25
Neural Network Training (nntraintool)
Neural Network
Input
Hidden
Output
Algorithms
Data Division: Random (dividerand)
Training: Levenberg-Marquardt (trainlm)
Performance: Mean Squared Error (mse)
Calculations: MATLAB
Progress
Epoch: 0 1 iterations 1000
Time: 0:00:02
Performance: 4.14e+03 1.34e+03 0.00
Gradient: 3.56e+04 1.64e+04 1.00e-07
Mu: 0.00100 0.0100 1.00e+10
Validation Checks: 0 0 6
Plots
Performance (plotperform)
Training State (plottrainstate)
Error Histogram (ploterrhist)
Regression (plotregression)
Fit (plotfit)
Plot Interval: 1 epochs
Training neural network...
Stop Training
Cancel
Workspace
Name Value Min Max
condition 112528x5 double <Too ... <Too ...
e 1x112528 double -60.29... 105.95...
golabi 112528x4 double NaN NaN
hiddenLayerSize 25 25 25
net 1x1 network
performance 25.4687 25.4687 25.4687
RUL 112528x1 double 0 148
t 1x112528 double 0 148
testPerformance 26.7404 26.7404 26.7404
testTargets 112528x1 double NaN NaN
tr 1x1 struct
trainFcn 'trainlm'
trainPerformance 25.1803 25.1803 25.1803
trainTargets 112528x1 double NaN NaN
valPerformance 25.5428 25.5428 25.5428
valTargets 112528x1 double NaN NaN
x 5x112528 double <Too ... <Too ...
y 112528x1 double -82.95... 152.58...
Busy
Ln 1 Col 1

Table 5-14. Performance Indices for models with one hidden layer

Neuron	Algorithm	RAE			MAE			R^2			RRSE			MAPE		
		training	testing	validation	Training	testing	validation	training	testing	validation	training	testing	validation	training	testing	validation
10	br	0.113	0.163	N/A	4.839	3.979	N/A	0.987	0.975	N/A	0.113	0.159	N/A	3.649	2.936	N/A
	lm	0.187	0.187	0.187	4.522	4.568	4.540	0.963	0.963	0.963	0.192	0.193	0.192	3.457	3.408	3.386
	scg	0.223	0.221	0.220	5.388	5.395	5.380	0.948	0.949	0.949	0.227	0.226	0.225	4.079	3.979	3.989
15	br	0.112	0.164	N/A	4.785	3.958	N/A	0.988	0.975	N/A	0.111	0.159	N/A	3.610	2.907	N/A
	lm	0.166	0.165	0.166	4.023	4.028	4.032	0.973	0.973	0.973	0.164	0.163	0.164	2.972	2.990	3.361
	scg	0.236	0.235	0.235	5.700	5.745	5.737	0.942	0.941	0.941	0.240	0.243	0.244	4.287	4.233	4.265
20	br	0.110	0.160	N/A	4.716	3.910	N/A	0.988	0.976	N/A	0.110	0.156	N/A	3.558	2.916	N/A
	lm	0.167	0.165	0.166	4.035	4.026	4.036	0.972	0.972	0.973	0.166	0.167	0.165	3.062	2.969	2.994
	scg	0.248	0.245	0.245	6.009	5.961	5.996	0.933	0.936	0.935	0.259	0.253	0.256	4.526	4.391	4.461
25	br	0.110	0.159	N/A	4.709	3.879	N/A	0.988	0.976	N/A	0.109	0.155	N/A	3.550	2.866	N/A
	lm	0.158	0.160	0.159	3.848	3.853	3.833	0.976	0.976	0.976	0.153	0.155	0.154	2.914	2.851	2.814
	scg	0.222	0.223	0.219	5.377	5.384	5.382	0.948	0.948	0.947	0.228	0.229	0.230	4.067	3.968	4.012
30	br	0.110	0.159	N/A	4.697	3.883	N/A	0.988	0.976	N/A	0.110	0.156	N/A	3.549	2.870	N/A
	lm	0.172	0.176	0.174	4.181	4.218	4.229	0.969	0.957	0.969	0.175	0.207	0.177	3.094	3.133	3.553
	scg	0.247	0.246	0.245	5.992	5.930	5.958	0.936	0.937	0.939	0.253	0.251	0.248	4.569	4.423	4.425
35	br	0.110	0.160	N/A	4.711	3.909	N/A	0.988	0.971	N/A	0.110	0.171	N/A	3.553	2.892	N/A
	lm	0.181	0.183	0.185	4.394	4.452	4.460	0.966	0.948	0.961	0.185	0.227	0.198	3.348	3.311	3.303
	scg	0.227	0.225	0.222	5.487	5.496	5.396	0.946	0.947	0.949	0.233	0.231	0.226	4.133	4.080	3.979
40	br	0.111	0.162	N/A	4.726	3.928	N/A	0.988	0.974	N/A	0.111	0.162	N/A	3.562	2.902	N/A
	lm	0.168	0.170	0.170	4.085	4.126	4.102	0.971	0.966	0.971	0.169	0.184	0.170	3.099	3.036	3.025
	scg	0.235	0.235	0.235	5.719	5.653	5.649	0.942	0.943	0.943	0.241	0.239	0.238	4.332	4.181	4.166

Table 5-15. Performance Indices for models with two hidden layers

Neuron	Algorithm	RAE			MAE			R^2			RRSE			MAPE		
		training	testing	validation	Training	testing	validation	training	testing	validation	training	testing	validation	training	testing	validation
10	br	0.107	0.158	N/A	4.595	3.845	N/A	0.989	0.976	N/A	0.107	0.154	N/A	3.381	3.232	N/A
	lm	0.159	0.160	0.159	3.852	3.872	3.852	0.976	0.976	0.976	0.154	0.154	0.156	2.842	2.861	3.231
	scg	0.219	0.220	0.219	5.316	5.316	5.319	0.949	0.949	0.949	0.226	0.227	0.225	4.032	3.976	3.955
15	br	0.107	0.158	N/A	4.556	3.839	N/A	0.989	0.970	N/A	0.106	0.172	N/A	3.435	2.826	N/A
	lm	0.166	0.165	0.166	4.023	4.028	4.032	0.973	0.973	0.973	0.164	0.163	0.164	2.972	2.990	3.361
	scg	0.236	0.234	0.235	5.735	5.655	5.689	0.942	0.944	0.943	0.241	0.237	0.239	4.341	4.180	4.202
20	br	0.106	0.157	N/A	4.543	3.828	N/A	0.989	0.971	N/A	0.106	0.169	N/A	3.425	2.803	N/A
	lm	0.162	0.164	0.163	3.931	3.978	3.956	0.974	0.973	0.973	0.161	0.164	0.164	2.892	3.331	2.936
	scg	0.217	0.218	0.220	5.258	5.312	5.354	0.949	0.949	0.948	0.225	0.225	0.228	3.996	3.941	3.984
25	br	0.110	0.159	N/A	4.709	3.879	N/A	0.988	0.976	N/A	0.109	0.155	N/A	3.550	2.866	N/A
	lm	0.164	0.165	0.163	3.983	4.003	3.977	0.974	0.971	0.973	0.163	0.169	0.165	2.940	2.957	3.303
	scg	0.230	0.230	0.229	5.568	5.566	5.571	0.944	0.944	0.944	0.236	0.237	0.236	4.109	4.088	4.533
30	br	0.106	0.156	N/A	4.524	3.764	N/A	0.989	0.973	N/A	0.105	0.165	N/A	3.409	2.765	N/A
	lm	0.160	0.159	0.159	3.877	3.894	3.894	0.975	0.975	0.975	0.157	0.157	0.157	2.937	2.888	2.877
	scg	0.235	0.231	0.234	5.690	5.663	5.688	0.942	0.943	0.943	0.241	0.239	0.238	4.266	4.219	4.206
35	br	0.105	0.155	N/A	4.508	3.774	0.000	0.989	0.973	N/A	0.105	0.166	N/A	3.313	3.198	0.000
	lm	0.158	0.159	0.159	3.835	3.866	3.862	0.976	0.974	0.975	0.154	0.161	0.158	2.911	2.837	2.853
	scg	0.214	0.214	0.213	5.183	5.224	5.182	0.950	0.950	0.949	0.222	0.223	0.226	3.952	3.897	3.867
40	br	0.106	0.155	N/A	4.534	3.757	0.000	0.989	0.976	N/A	0.105	0.155	N/A	3.332	3.171	0.000
	lm	0.165	0.165	0.165	3.994	4.009	4.020	0.973	0.970	0.972	0.164	0.175	0.168	3.033	2.963	2.978
	scg	0.227	0.227	0.225	5.502	5.493	5.476	0.945	0.945	0.942	0.234	0.235	0.241	4.168	4.071	4.039

The error histogram of the final model with 25 neurons is presented in Figure 5-12. It can be seen from the bars that most of the errors are oscillating between -7 and 4 years in all the training, testing and validation phases which shows that the model predicted remaining useful life of the pipeline well. The number of pipe cases used in training, testing and validation phases are divided based on 70%, 15% and 15% of the total pipelines considered in this study.

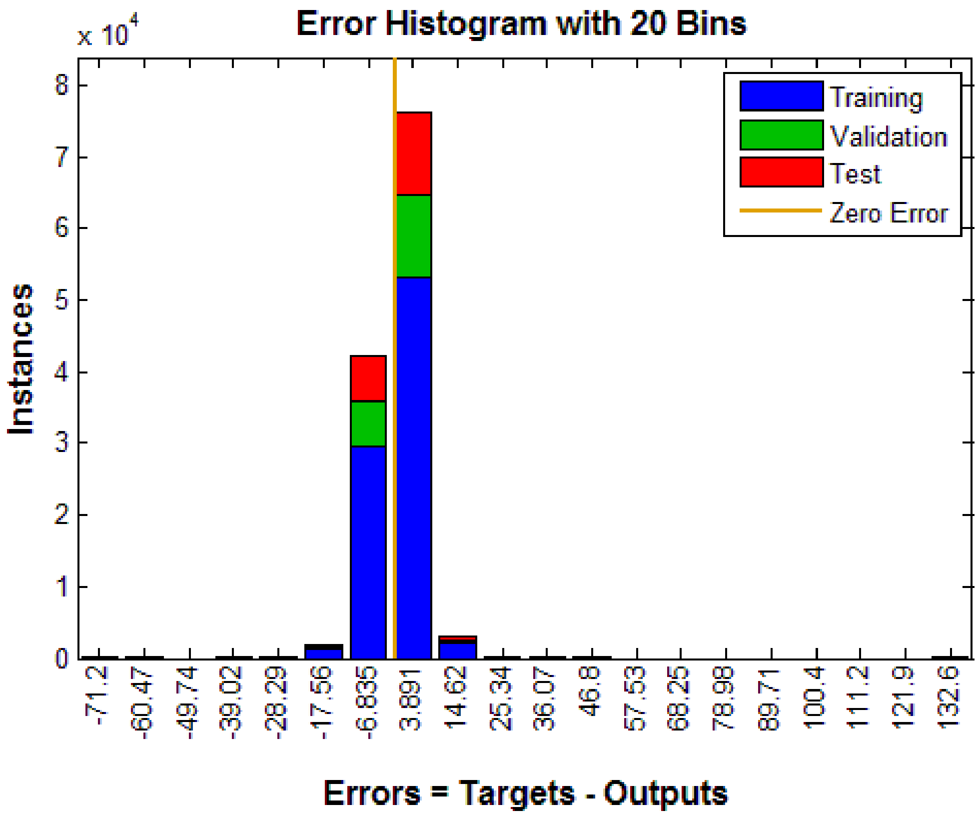


Figure 5-12.Error Histogram for final model

The coefficient of determination values of training, testing and validation phases are displayed in Figure 5-13. The horizontal axis and vertical axis show target versus output that are remaining useful lives here and are in years. The R^2 value of all data is displayed as well. The fitted line for all data is output = 0.97 × target + 4.5, and R^2 value is 98.56% which shows that the outputs are very close to target values. The R^2 value is more than

98% in all the training, testing and validation phases which is a proof that the model is able to predict 98% of the future outcomes accurately.

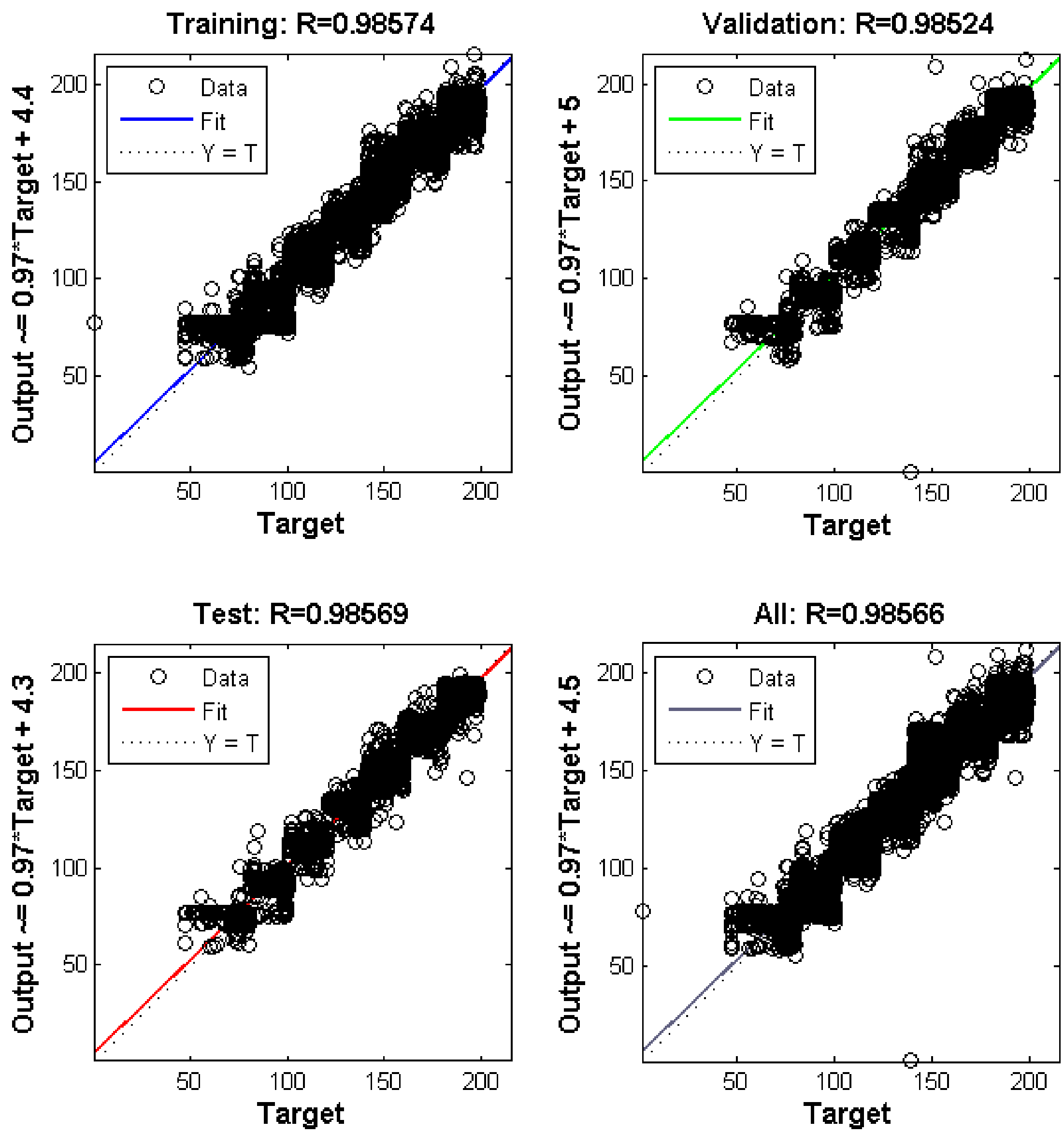


Figure 5-13. Coefficient of determination (R^2) for final model

Table 5-16 shows the sample data input of diameter, breakage rate, length, material and condition along with the estimated and predicted output values of the proposed neural network model.

Table 5-16. Sample input and output data for ANN model

Pipe ID	Input					Output	
	diameter	breakage rate	Length	material	condition	Estimated RUL	Predicted RUL
1	200	0	3.49	1.67	2.469	127	120.85
2	150	2.42	17.95	1.67	2.995	127	122.88
3	20	0	22.56	1.67	2.469	127	120.64
4	200	0	10.30	1.67	2.469	128	120.77
5	150	0	10.88	1.67	2.469	128	122.61
6	150	0	70.13	1.67	2.469	128	122.44
7	200	0	55.36	1.67	2.469	128	120.44
8	200	0	73.69	1.67	2.469	127	120.41
9	200	0	0.55	1.67	2.469	127	120.89
10	150	0	44.92	1.67	2.469	128	122.43
11	150	0	132.31	1.67	2.469	128	122.88
12	150	0	55.39	1.67	2.469	128	122.42
13	150	0	19.56	1.67	2.469	128	122.54
14	150	0	150.37	1.67	2.469	128	123.07
15	150	0	27.23	1.67	2.469	128	122.49
16	150	0	16.26	1.67	2.469	128	122.56
17	200	0	49.34	1.67	2.469	128	120.46
18	200	0	67.12	1.67	2.469	127	120.41
19	200	0	11.98	1.67	2.469	127	120.75
20	200	0	43.32	1.67	2.469	126	120.84
21	200	0	11.31	1.67	2.469	126	120.49
22	200	0	7.10	1.67	2.469	128	120.76
23	200	0	79.28	1.67	2.469	128	120.81
24	150	0	5.41	1.67	2.469	128	120.41
25	150	0	5.76	1.67	2.469	128	122.66
26	150	0	37.29	1.67	2.469	128	122.66
27	150	0	47.07	1.67	2.469	128	122.44
28	150	0	87.25	1.67	2.469	128	122.42
29	200	0	15.84	1.67	2.469	128	122.52
30	200	0	24.44	1.67	2.469	128	120.71
31	200	0	5.23	1.67	2.469	128	120.63
32	150	0	10.66	1.67	2.469	127	120.83
33	150	0	65.64	1.67	2.469	127	122.61
34	150	0	16.30	1.67	2.469	127	122.43
35	150	0	65.06	1.67	2.469	127	122.56
..	..	..	..	..	..	..	..

Moreover, GRNN is applied to the data of the city of Montreal and the developed equation and the results are summarized in Table 5-17.

$$RUL = 201.76 - 36.42\, condition + 3.67\, breakage\ rate - 0.028\, diameter + 10.14\, material - 0.003\, length \quad (5\text{-}2)$$

Table 5-17. Performances indices when applying GRNN

Performance index	GRNN	Selected model
RAE	0.397	0.159
MAE	8.388	3.844
R^2	0.806	0.976
RRSE	0.440	0.153
MAPE	9.714	2.86

As can be seen from comparison of two methods the coefficient of determination is lower in GRNN which shows that the model is able to predict only 80% of the data accurately which is low in comparison to 97.6% of the proposed ANN model. Moreover, all of the other performance indices such as RAE, MAE, RRSE and MAPE are higher in GRNN in comparison to applying Levenberg–Marquardt algorithm which confirms that the selected algorithm predicts remaining useful life more precisely than GRNN. As stated in section 2.6.5, the sole drawback of GRNN is that it is not able to ignore unrelated inputs itself. Therefore, GRNN is not chosen in problems with more than 5 to 6 related inputs. In remaining useful life prediction, five input parameters of condition, diameter, material, length and breaker rate are considered which makes GRNN incompetent for function approximation.

It can be seen from Figure 5-14, the GRNN overestimates RUL when age is more than 70 years old. When the pipe ages between 50 to 70 years, GRNN predicts remaining useful life very well. Moreover, the remaining useful life is underestimated when pipe is less than 30 years. Based on the available performance indices, it could be concluded that the selected model which uses Levenberg–Marquardt algorithm to predict data works better through this problem.

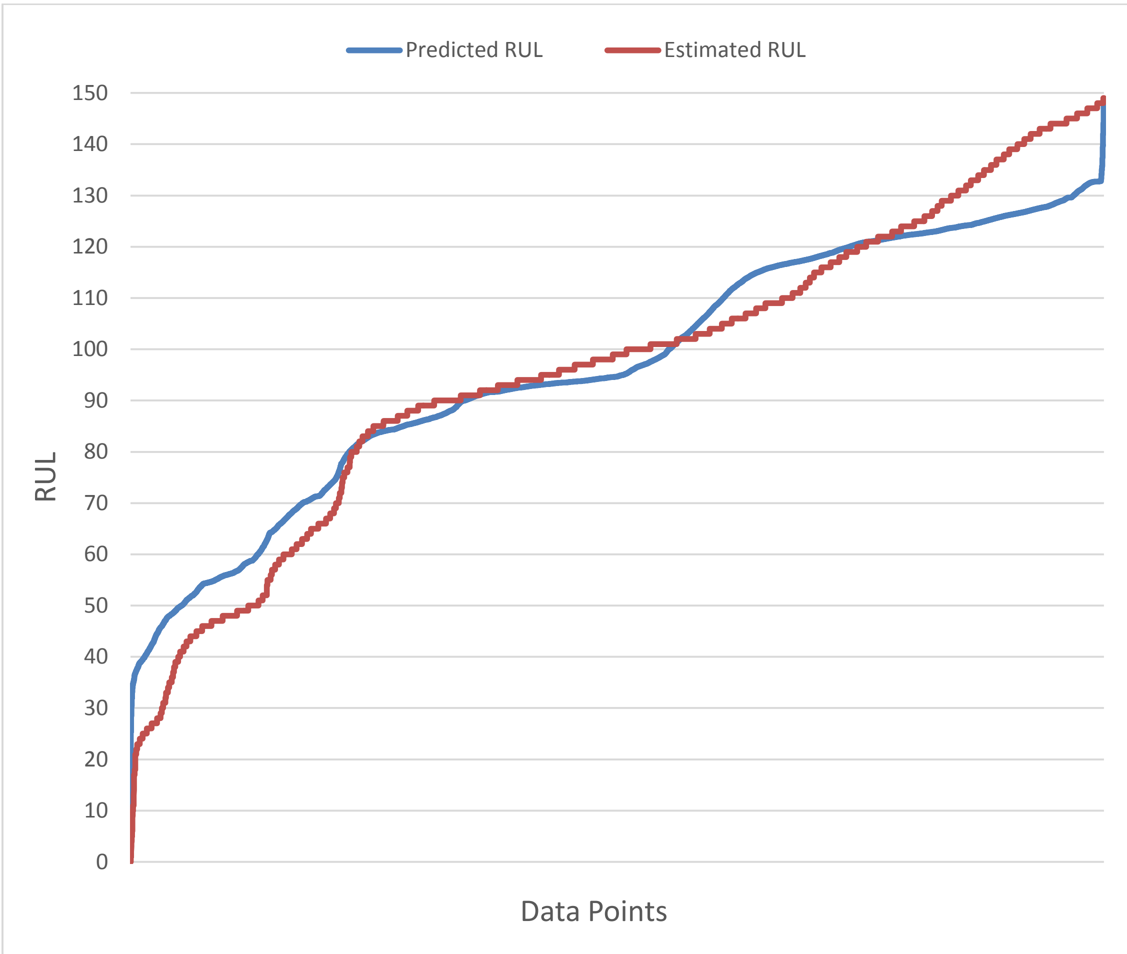


Figure 5-14. Estimated and Predicted RUL vs data points using GRNN

5.4. Budget Allocation Model

The optimal scheduling for replacement and rehabilitation of individual water mains is an important challenge that has been extensively focused on in the past twenty years. In majority of cases, a forecasting model of future breakage rates, remaining useful life or condition of the pipeline is attached to the optimal scheduling pattern. There are quite a few researches concentrating on network of water pipes, while majority of efforts are devoted to optimal planning for individual pipelines. This research will focus on optimal scheduling for a whole water network distribution of a city through optimal scheduling of each pipe segment. In this research, a method is proposed for optimal scheduling of individual pipes in a network while considering future number of breaks of a pipeline. This method is not restricted to any specific planning horizon length since the planning horizon will directly affect the number of breaks. However, some modification should be taken for the budget and costs due to the time value of the money. Moreover, unanticipated changing conditions of the pipelines should be considered for lengthy planning horizons. The proposed method is not limited to any specific break prediction model because it solely needs the number of breaks for each pipeline in the network in the predefined planning horizon. As mentioned earlier, $K_{i,t}$ is the predicted number of breaks in pipe i at year t and four different costs are observed to be associated with failure of each pipe section. They are cost of failure repair by C_i^{repair}, cost of disruption, time loss, pollution, loss of business by C_i^{social}, cost of water loss by $C_i^{water\ loss}$ and cost of pipe replacement, which is assumed to have two components of mobilization cost denoted by M, and the length-unit cost denoted by Cr_i. The mobilization costs cover cost of setting up the job site, signage, discovery and marking of adjacent infrastructure while Cr_i depends on pipe material and diameter (Nafi and Kleiner, 2010).

Table 5-18. Scenarios and their associated costs

	Scenario for each pipeline	Associated Cost
1	Replacement	$M + Cr_i l_i$
2	Rehabilitation: Open Trench	$C_i^{repair\ major}$
3	Rehabilitation: Trenchless	$C_i^{repair\ minor}$
4	No Action	$C_i^{water\ loss} + C_i^{social}$
5	Need Nothing	0

Consequently, the total cost associated with pipe replacement timing will be

$$C_{total} = \sum_{i=1}^{n} [K_{i,t}(C_i^{repair\ major}\ or\ C_i^{repair\ minor}\ or\ C_i^{water\ loss}\ or\ C_i^{social})\ or\ (M + Cr_i l_i)] \quad 5\text{-}3$$

The number of breaks for each network is specific for that network, therefore in this study the future breaks for city of Montreal should be considered. Karimian (2015) proposed a break forecasting model which predicts disruptions of Montreal by 89.35% accuracy. Therefore, this model will be applied to find the future number of breaks in different planning horizon. The proposed relationship is:

$$K_{i,t} = 0.017785 \frac{L^{1.5} M^2 A^{0.5}}{D^2} + 6.1833 \times 10^{-6} \frac{L^{1.5} A^2}{D M^2} \ln\left(\frac{D}{L}\right)^{1.5} \quad 5\text{-}4$$

L is length, M is material, A is age and D is diameter. As stated in Chapter 3, the objective of this model is to maximize the use of budget for water network that is 82.3 million dollar based on the literature. Therefore, pipe segments should be prioritized for different setups based on their breakage rate and assumed cost for each scenario. The input data for GA model is an excel sheet with all of the four costs and the breakage rate of a specific planning horizon for each pipe segments as displays in Figure 5-15.

FILE HOME INSERT PAGE LAYOUT FORMULAS DATA REVIEW VIEW DEVELOPER NITRO PRO 9

F4 150

	E	F	G	N	R	S	T	U	W	AB	AI
3	Age	Diameter	Material	Length	Cr	M+crL	Mnor	major	No action	K (t=5 yrs)	
4	23	150	DI	17.951885	350	8283.159687	3000	5000	2600	0.0049435	
5	6	150	CI	3.1761009	350	3111.635313	3000	5000	2600	0.000104	
6	69	150	CI	70.268634	350	26594.02179	3000	5000	2600	0.0494186	
7	6	150	CI	14.118374	350	6941.430847	3000	5000	2600	0.0009554	
8	69	150	CI	12.555112	350	6394.289272	3000	5000	2600	0.0062384	
9	6	150	CI	122.73616	350	44957.6558	3000	5000	2600	0.023762	
10	6	150	CI	7.5790477	350	4652.666693	3000	5000	2600	0.000379	
11	6	150	CI	105.96034	350	39086.11913	3000	5000	2600	0.0191004	
12	6	150	CI	120.54877	350	44192.07022	3000	5000	2600	0.0231355	
13	68	150	CI	136.3419	350	49719.66327	3000	5000	2600	0.098221	
14	84	150	CI	57.466973	350	22113.4405	3000	5000	2600	0.0486657	
15	86	150	CI	142.95999	350	52035.99575	3000	5000	2600	0.1169429	
16	86	150	CI	127.12347	350	46493.21545	3000	5000	2600	0.1066105	
17	84	150	CI	15.254526	350	7339.084274	3000	5000	2600	0.0104865	
18	91	150	CI	31.757044	350	13114.96553	3000	5000	2600	0.0279522	
19	69	200	CI	145.87767	360	54515.96206	3000	5000	2600	0.072205	
20	90	150	CI	38.756969	350	15564.93925	3000	5000	2600	0.0344554	
21	86	150	CI	109.93056	350	40475.69657	3000	5000	2600	0.0942416	
22	91	150	CI	148.78191	350	54073.66894	3000	5000	2600	0.1239991	
23	95	250	CI	52.030099	380	21771.43772	3000	5000	2600	0.0312841	
24	92	150	CI	152.46853	350	55363.98416	3000	5000	2600	0.126676	
25	92	150	CI	158.87551	350	57606.42824	3000	5000	2600	0.1299506	
26	92	150	CI	125.2832	350	45849.1191	3000	5000	2600	0.1103684	
27	85	150	CI	197.77092	350	71219.82245	3000	5000	2600	0.1442484	
28	3	150	CI	153.54271	350	55739.95014	3000	5000	2600	0.0234405	
29	3	150	CI	155.14123	350	56299.42971	3000	5000	2600	0.0238063	
30	95	150	CI	202.92491	350	73023.71685	3000	5000	2600	0.1462718	

... original Sheet1

READY

Figure 5-15. Sample input data for optimization model

The GA tries to minimize the following fitness function and chooses one scenario for each pipe considering the cost, breakage rate and total constrained budget.

$$BEST = 82.3 \times 10^6 - \sum_{i=1}^{n} [K_{i,t}(C_i^{repair\ major}\ or\ C_i^{repair\ minor}\ or\ C_i^{water\ loss}\ or\ C_i^{social})\ or\ (M + Cr_i l_i)] \tag{5-5}$$

GA does multiple iteration to find the best solution as displayed in Figure 5-16. The outcome of GA model would be an excel sheet in which rows represent pipe segments and columns are different scenarios. Selected scenario for each pipe is identified in each row as shown in Figure 5-17.

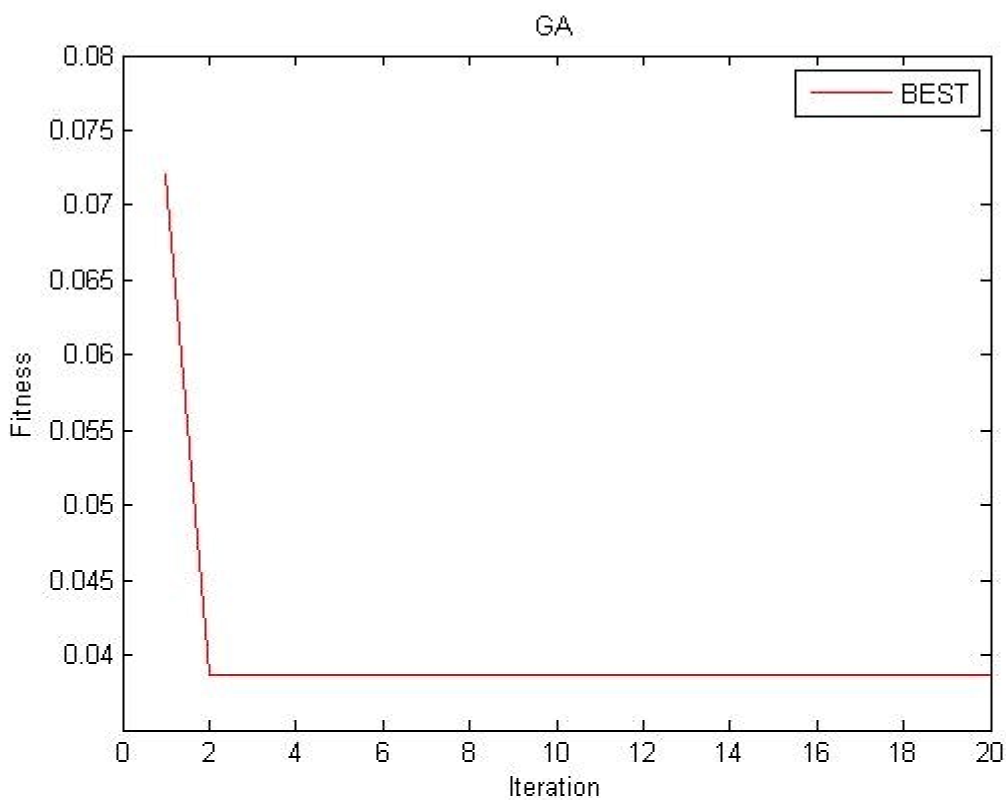
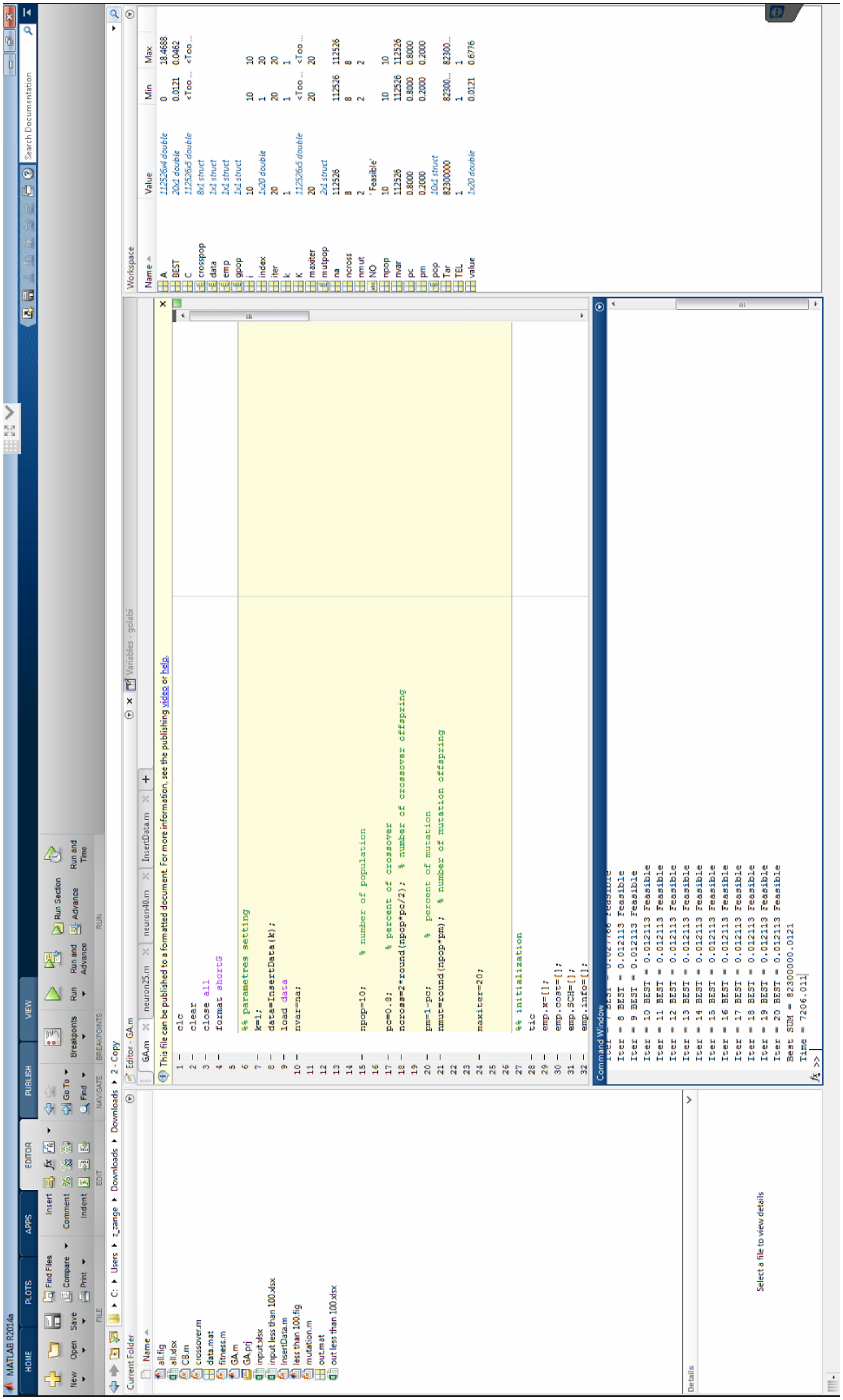
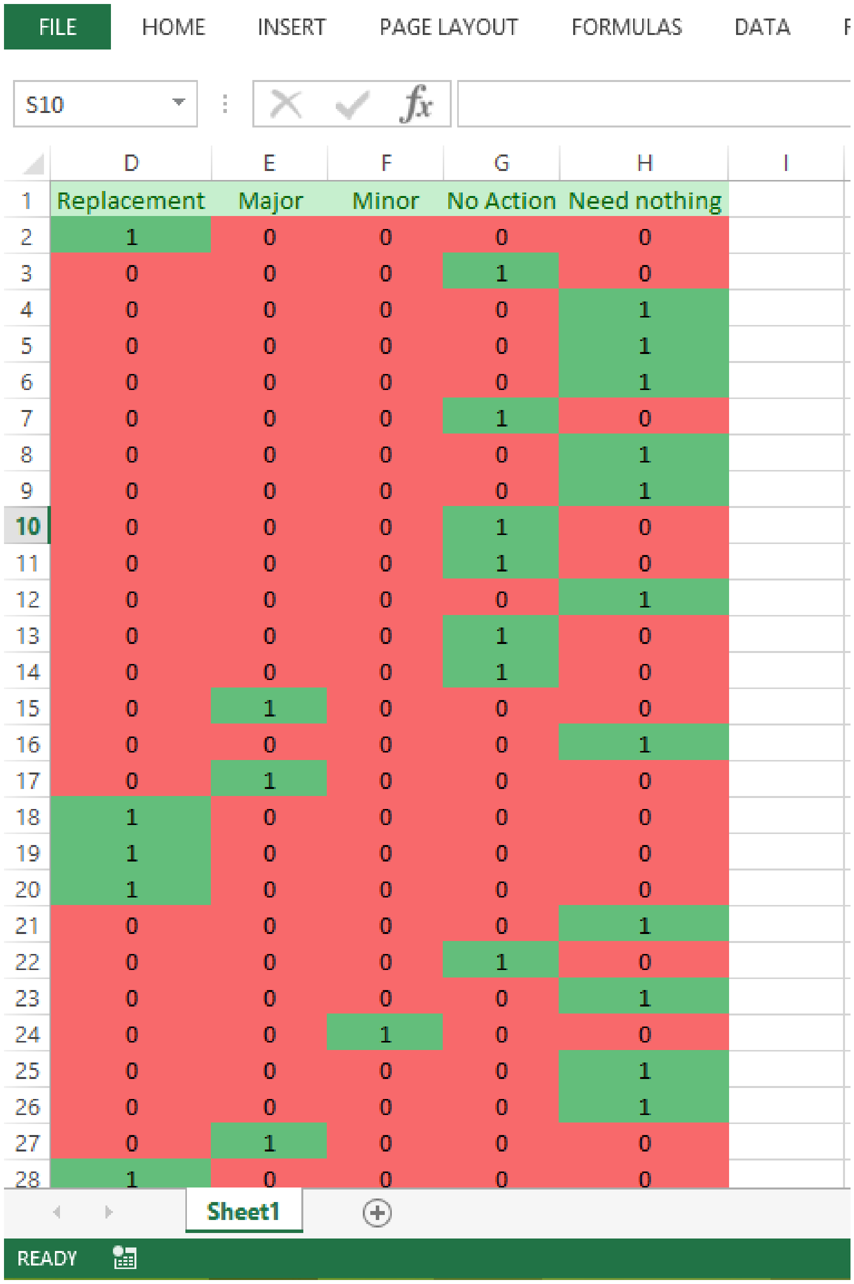


Figure 5-16. Fitness function in different iterations


MATLAB R2014a
clc
clear
close all
format shortG
%% parametres setting
k=1;
data=InsertData(k);
load data
nvar=na;
npop=10;   % number of population
pc=0.8;   % percent of crossover
ncross=2*round(npop*pc/2); % number of crossover offspring
pm=1-pc;   % percent of mutation
nmut=round(npop*pm); % number of mutation offspring
maxiter=20;
%% initialization
tic
emp.x=[];
emp.cost=[];
emp.SCH=[];
emp.info=[];
Command Window
Iter = 8 BEST = 0.012113 Feasible
Iter = 9 BEST = 0.012113 Feasible
Iter = 10 BEST = 0.012113 Feasible
Iter = 11 BEST = 0.012113 Feasible
Iter = 12 BEST = 0.012113 Feasible
Iter = 13 BEST = 0.012113 Feasible
Iter = 14 BEST = 0.012113 Feasible
Iter = 15 BEST = 0.012113 Feasible
Iter = 16 BEST = 0.012113 Feasible
Iter = 17 BEST = 0.012113 Feasible
Iter = 18 BEST = 0.012113 Feasible
Iter = 19 BEST = 0.012113 Feasible
Iter = 20 BEST = 0.012113 Feasible
Best SUM = 82300000.0121
Time = 7206.011



	D	E	F	G	H
1	Replacement	Major	Minor	No Action	Need nothing
2	1	0	0	0	0
3	0	0	0	1	0
4	0	0	0	0	1
5	0	0	0	0	1
6	0	0	0	0	1
7	0	0	0	1	0
8	0	0	0	0	1
9	0	0	0	0	1
10	0	0	0	1	0
11	0	0	0	1	0
12	0	0	0	0	1
13	0	0	0	1	0
14	0	0	0	1	0
15	0	1	0	0	0
16	0	0	0	0	1
17	0	1	0	0	0
18	1	0	0	0	0
19	1	0	0	0	0
20	1	0	0	0	0
21	0	0	0	0	1
22	0	0	0	1	0
23	0	0	0	0	1
24	0	0	1	0	0
25	0	0	0	0	1
26	0	0	0	0	1
27	0	1	0	0	0
28	1	0	0	0	0

Figure 5-17. Sample outcome of the GA model

5.5. Two-tier Inspection Planning Model

A comparative and comprehensive study of methods for detection the location of leaks and identification of defects in water distribution networks are presented in Chapter 2. The section encompasses 22 technologies and summarizes their respective advantages and limitations. The technologies utilized in these methods are grouped in five categories; (1) visual, (2) electromagnetic and radio frequency, (3) acoustic and vibration, (4) ultrasound and (5) other techniques. Given the diverse circumstances under which WDNs are operating, no single method is capable of providing an accurate assessment of the pipe condition in all such cases. To address this problem, a hybrid approach is proposed in this section which integrates acoustic and Infrared technologies. The proposed model has 2 Tiers; in tier one less costly and easy to used equipment are employed for overall condition assessment of the network such as Infrared technology. Tier two makes full used of the result obtained from tier one and utilizes more accurate and relatively high in cost method of condition assessment only for pipe segments and zones where the condition is worse than the rest and acquires attention.

Use of Infrared has been reported on site. This method consists of an infrared scanner and a camera. The scanner measures temperature changes and produces thermographic images. When a defect happens in pipe, the water starts passing through the wall pipe inside the soil, this causes a decrease in temperature of the surrounding soil. As mentioned in section 2.3.3 about LeakfinderRT method, two transmitters are installed in two access points on the pipe. They transmit radio frequency signals through the pipe from both directions. The signals propagate through the pipe and reflect back when they reach the leak. Equations 2-1 and 2-2 calculate the distance of the leak from each access points. There are several advantages and a number of limitations for Infrared technology and LeakfinderRT in literature. They are summarized in Table 5-19.

.

Table 5-19. Advantages and limitations of Infrared and LeakfinderRT

Method	Advantages	Limitations
Infrared technology	1. Sensitive, reliable and accurate 2. Trenchless; No direct contact and intrusion is required 3. Independent of the pipeline material 4. Needs minimum instrumentations 5. Allow rapid scanning of objects 6. Easy to operate	1. Unable to measure depth and the size of the leak 2. Affected by ground cover, moisture content and wind 3. Aff ected by properties of surrounding ground 4. Limited detection ability below the ground water table 5. A temperature difference is necessary to identify the anomalies
LeakfinderRT	1. Improved resolution in images for narrow-band leak signals 2. Works in all pipes irrespective of diameter, geometry, material and etc. 3. Good for small leaks and small pipes and noisy areas 4. Assesses the structural condition of mains 5. Identifies multiple leaks 6. Rapid and Accurate 7. Works in harsh weather condition 8. Trenchless non-destructive technique	1. Not applicable in discontinuity 2. Cannot detect leak size 3. Pipeline size and material affect sensor spacing 4. Susceptible to interference from low-frequency vibration, like pumps and road traffic

In the main model, the condition of the pipelines are identified at first module and RUL are calculated. Then the pipes which needs maintenance are determined. If any pipes is detected to be in poor to critical condition and its useful life is about to end, then the inspections of the old pipes were performed. Infrared inspection is completed at first tire and suspicious areas were identified. Subsequently, the detected areas were inspected once more with LeakfinderRT to make sure of the existence of the leak. If both methods confirm one defect, the excavation and maintenance will be performed at the detected area. This will reduce the cost of excavation and inspection in a great deal. Comparing the hybrid model with existing common methods, it could be concluded that the model reduces the cost of performing both methods for the whole areas. It also eliminates the cost of false excavations due to the inaccurate inspections. It is more precise because two different technologies have been used for inspection of the whole areas.

5.6. Model implementation to a case study

The proposed framework and the associated sub-models were applied to the historical data of the city of Montreal as illustrated in Figure 5-18. In the first sub-model, the historical data were considered as the input for condition index model. After calculation of pipe condition, it is used along historical data to estimate the remaining useful life of the pipelines. Next step comes with utilizing the predicted remaining useful life, estimated condition and historical data to find rehabilitation/replacement strategies for different pipe segments in water distribution network. These strategies are checked through acquired inspection results and final intervention plans are generated. At the end, the operator is able to take the required action for the distribution network.

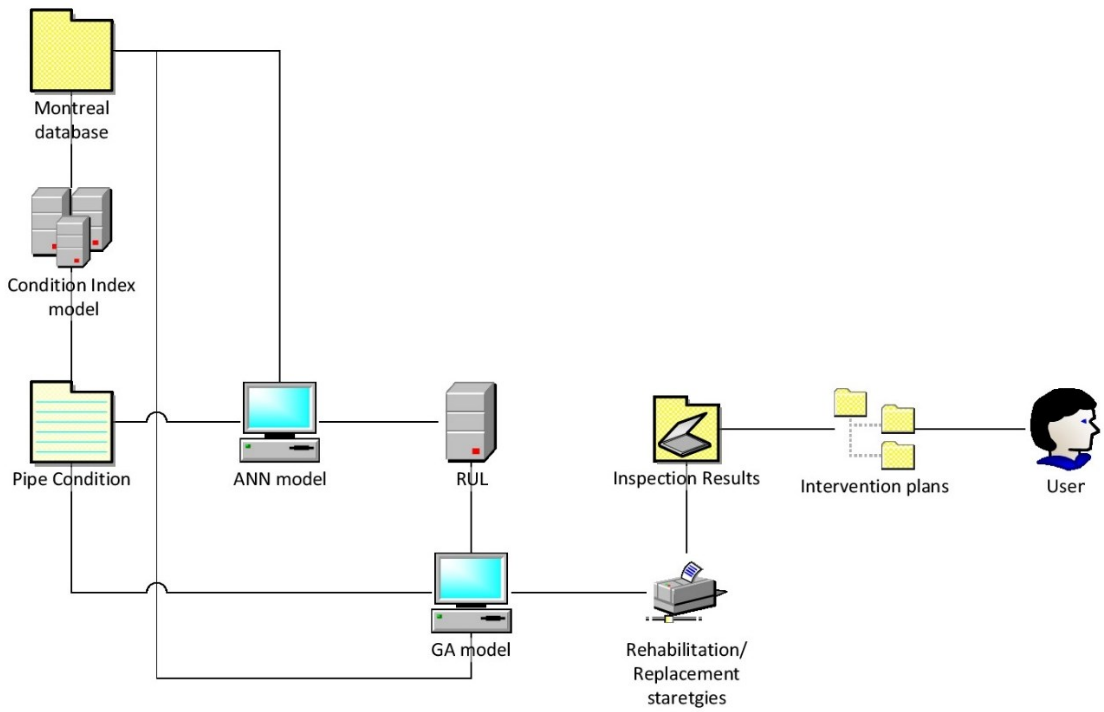
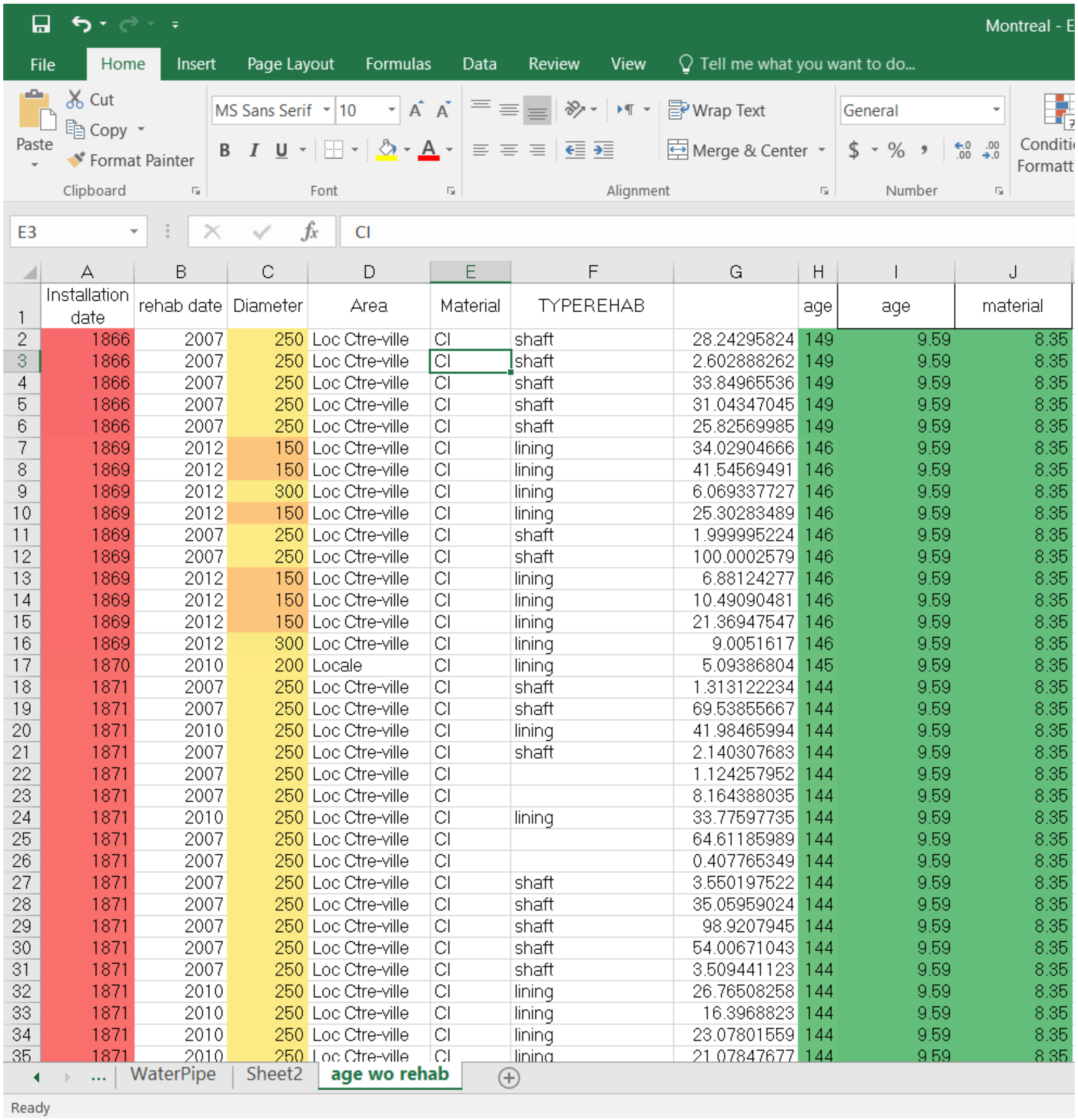


Figure 5-18. Proposed framework

The first step is calculating the condition index. Data are inserted into an excel sheet as Figure 5-19 and condition is calculate based on equation 5-1.



	A	B	C	D	E	F	G	H	I	J
1	Installation date	rehab date	Diameter	Area	Material	TYPEREHAB		age	age	material
2	1866	2007	250	Loc Ctre-ville	CI	shaft	28.24295824	149	9.59	8.35
3	1866	2007	250	Loc Ctre-ville	CI	shaft	2.602888262	149	9.59	8.35
4	1866	2007	250	Loc Ctre-ville	CI	shaft	33.84965536	149	9.59	8.35
5	1866	2007	250	Loc Ctre-ville	CI	shaft	31.04347045	149	9.59	8.35
6	1866	2007	250	Loc Ctre-ville	CI	shaft	25.82569985	149	9.59	8.35
7	1869	2012	150	Loc Ctre-ville	CI	lining	34.02904666	146	9.59	8.35
8	1869	2012	150	Loc Ctre-ville	CI	lining	41.54569491	146	9.59	8.35
9	1869	2012	300	Loc Ctre-ville	CI	lining	6.069337727	146	9.59	8.35
10	1869	2012	150	Loc Ctre-ville	CI	lining	25.30283489	146	9.59	8.35
11	1869	2007	250	Loc Ctre-ville	CI	shaft	1.999995224	146	9.59	8.35
12	1869	2007	250	Loc Ctre-ville	CI	shaft	100.0002579	146	9.59	8.35
13	1869	2012	150	Loc Ctre-ville	CI	lining	6.88124277	146	9.59	8.35
14	1869	2012	150	Loc Ctre-ville	CI	lining	10.49090481	146	9.59	8.35
15	1869	2012	150	Loc Ctre-ville	CI	lining	21.36947547	146	9.59	8.35
16	1869	2012	300	Loc Ctre-ville	CI	lining	9.0051617	146	9.59	8.35
17	1870	2010	200	Locale	CI	lining	5.09386804	145	9.59	8.35
18	1871	2007	250	Loc Ctre-ville	CI	shaft	1.313122234	144	9.59	8.35
19	1871	2007	250	Loc Ctre-ville	CI	shaft	69.53855667	144	9.59	8.35
20	1871	2010	250	Loc Ctre-ville	CI	lining	41.98465994	144	9.59	8.35
21	1871	2007	250	Loc Ctre-ville	CI	shaft	2.140307683	144	9.59	8.35
22	1871	2007	250	Loc Ctre-ville	CI		1.124257952	144	9.59	8.35
23	1871	2007	250	Loc Ctre-ville	CI		8.164388035	144	9.59	8.35
24	1871	2010	250	Loc Ctre-ville	CI	lining	33.77597735	144	9.59	8.35
25	1871	2007	250	Loc Ctre-ville	CI		64.61185989	144	9.59	8.35
26	1871	2007	250	Loc Ctre-ville	CI		0.407765349	144	9.59	8.35
27	1871	2007	250	Loc Ctre-ville	CI	shaft	3.550197522	144	9.59	8.35
28	1871	2007	250	Loc Ctre-ville	CI	shaft	35.05959024	144	9.59	8.35
29	1871	2007	250	Loc Ctre-ville	CI	shaft	98.9207945	144	9.59	8.35
30	1871	2007	250	Loc Ctre-ville	CI	shaft	54.00671043	144	9.59	8.35
31	1871	2007	250	Loc Ctre-ville	CI	shaft	3.509441123	144	9.59	8.35
32	1871	2010	250	Loc Ctre-ville	CI	lining	26.76508258	144	9.59	8.35
33	1871	2010	250	Loc Ctre-ville	CI	lining	16.3968823	144	9.59	8.35
34	1871	2010	250	Loc Ctre-ville	CI	lining	23.07801559	144	9.59	8.35
35	1871	2010	250	Loc Ctre-ville	CI	lining	21.07847677	144	9.59	8.35

Figure 5-19.Sample Excel sheet calculation of Condition

Statistical specifications of the condition index of the city of Montreal are tabulated in Table 5-20. The maximum, minimum, median and average of the data are calculated for the entire water network.

Table 5-20.Data Specification of condition Index in city of Montreal

Condition Index	
Min	0.741
Max	7.750
Average	4.306
Median	4.985

The condition of the pipe segments are classified based on Table 5-13 into six groups from excellent to critical. The distribution of the condition of pipelines are illustrated in

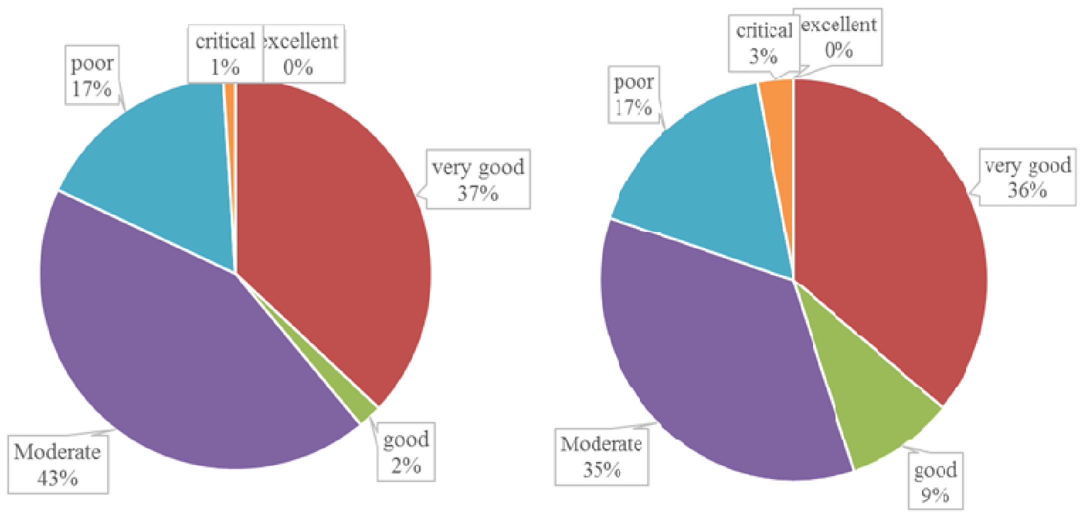


Figure 5-20.

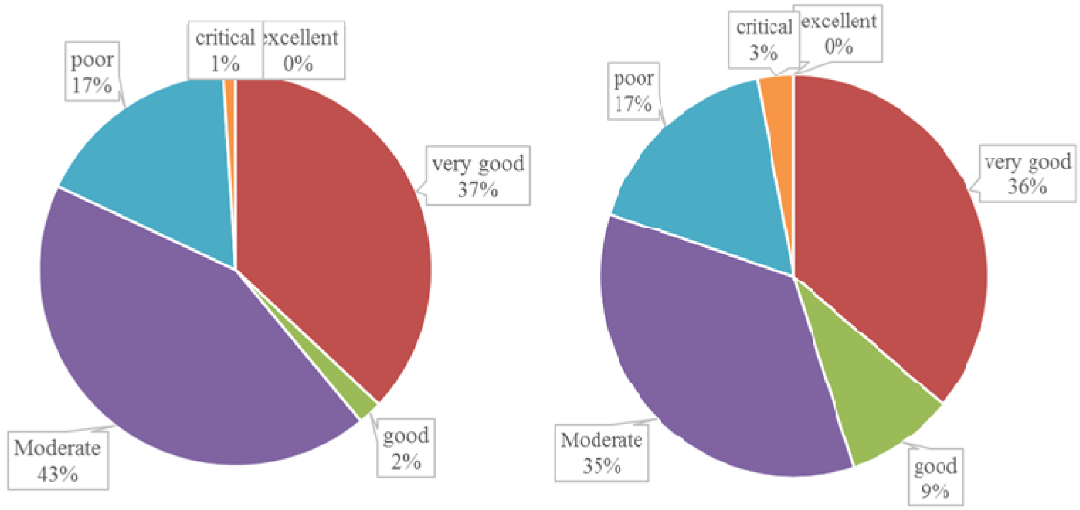


Figure 5-20. Distribution of condition in Montreal's water network from proposed mdoel (left) and 2016 Canadian Infrastructure Report card (right)

On second phase, ANN model uses condition and other physical properties of the pipe segments including breakage rate, pipe diameter, length, and material to estimate the remaining useful life of the pipeline. The target values of the remaining useful life are calculated based on the proposed equation in section 3.4. Figure 5-21 displays the estimated RUL and predicted RUL through neural network model for all the pipe segments over the network. There are some drops in estimated RULs that are associated to the fact that the expansions of the network have performed in multiple times. Since other parameters are considered in predicted RUL; therefore, it is smoother than Estimated remaining useful life. It can be seen that the estimated and predicted residual life of the pipelines are equal in several cases or are approximately in near vicinity of each other. This shows the competence of model in predicting the remaining useful life of water pipes.

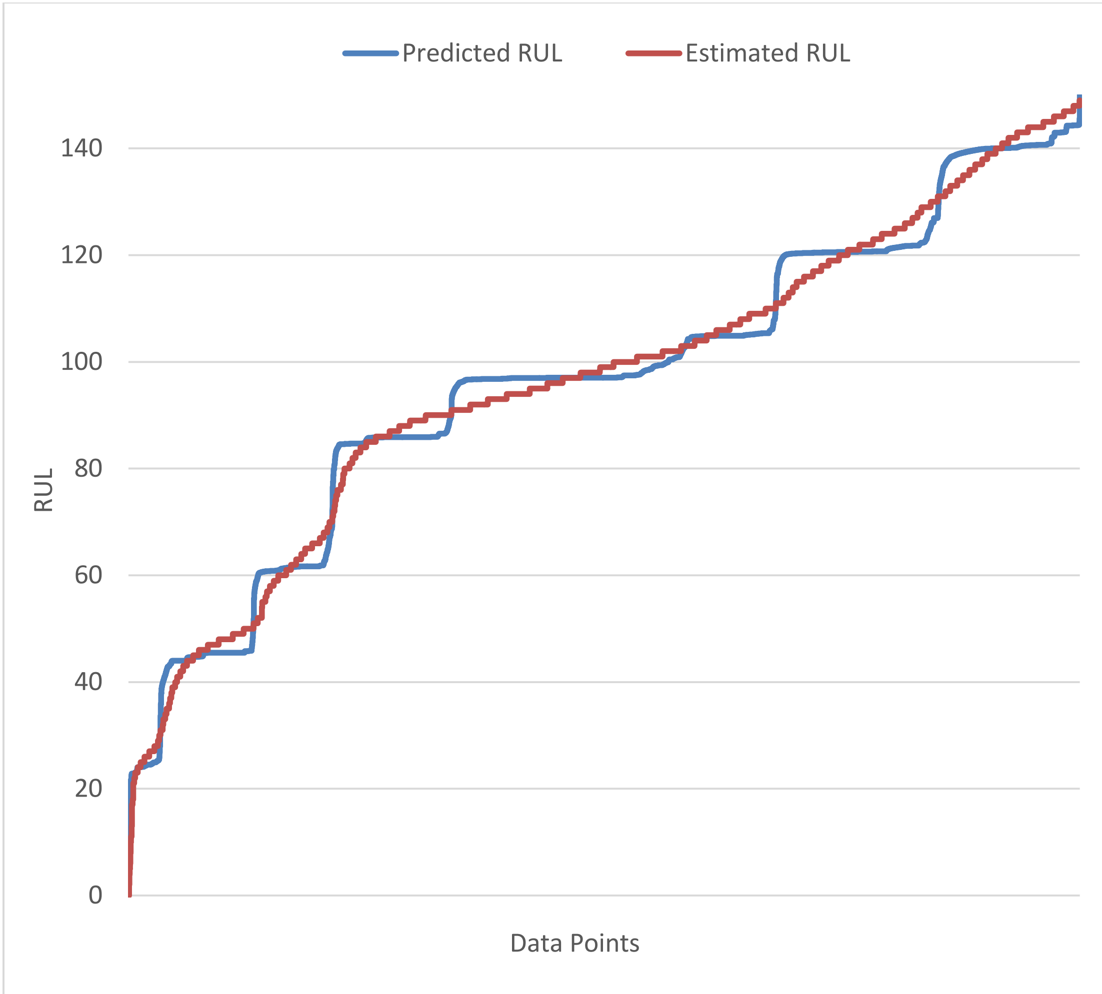


Figure 5-21. Estimated and Predicted RUL vs data points using LM algorithm

The distribution of remaining useful life of the entire network of Montréal is displayed in Figure 5-22. It can be seen that 35% of the pipelines have remaining useful life of 80-100 years while 40% have life expectancy of more than 100 years. This is due to the gradual maintenance that the pipelines are undergone during their lifetime. 5% of the pipelines are expected to work for about 20-40 years if situations stay the same. There are 1% of the pipelines with residual life of less than 20 years. Detailed percentage and number of pipe segments are shown in Table 5-21.

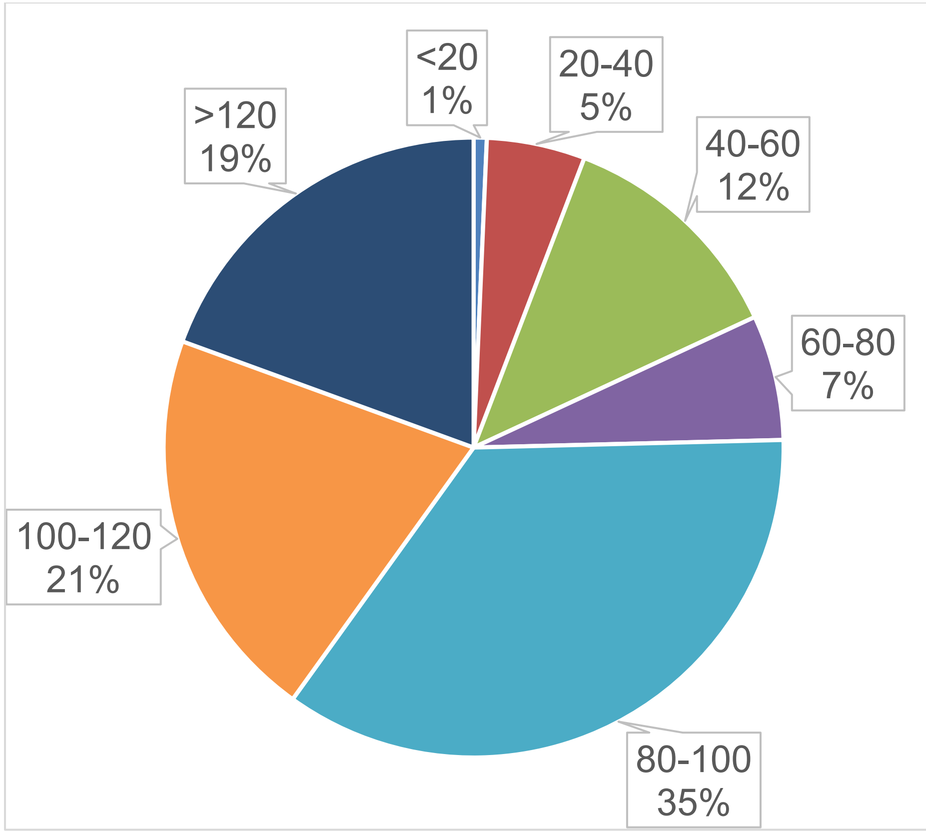


Figure 5-22. Distribution of Remaining useful life in Montreal's water network

Table 5-21. Remaining useful life of the network

Remaining useful life	Percentage	Data point
0 – 20 yrs	0.7%	768
20 – 40 yrs	5.1%	5,777
40 – 60 yrs	12.3%	13,800
60 – 80 yrs	6.5%	7,348
80 - 100 yrs	35.3%	39,734
100 - 120 yrs	20.6%	23,234
More than 120 yrs	19.4%	21,867
	100 %	112,528

There are 768 pipelines with remaining useful life of less than 20 years, which should be under consideration and need inspection every year to prevent from disastrous failures and sudden shutdown of the system. The total length of these old segments is 24.98 km, which is 0.46% of the total length of the network. Knowing the expected time of failure of a pipeline through having their remaining useful life gives the operator the opportunity to replace the pipe before it causes social and water loss costs in addition to the cost of replacement of the segment. Specification of the pipes that need to be replaced in near future are given in Table 5-22.

Table 5-22. Specification of the pipes with RUL less than 20 years

Material	Diameter (mm)	Installation date	Length (m)	Number of Breaks
CI	150 - 600	1862 - 1885	0.15 - 1377.5	1 - 9

On third phase, after analysis of the ANN model is completed and remaining useful life is identified, the budget allocation model will be applied to figure out the necessary strategies for network. This model is able to cover different planning horizons. In this network, the planning horizons of 20, 30 and 40 years are considered. The number of pipe segments that need each measurement is summarized in Table 5-23. As can be seen the number of pipes that need to be replaced are increasing from 2035 to 2045 because as time passes, more segments will reach end of their useful life.

Table 5-23. Number of pipes that needs different measurements

Planning year	Replacement	Rehabilitation (Open Trench)	Rehabilitation (Trenchless)	No Action: water loss
2035	798	28034	35363	28119
2040	1555	26765	30529	27180
2045	2174	22705	22083	22352

Table 5-24 shows the length of pipelines for each scenarios of the model. It can be seen that 30.70 km of the pipelines need to be replaced while 1156.59 km are in need of major rehabilitation. 1453.52 km of the network are in need of minor maintenance while 1166.08

are suffering from future tiny leakage and water loss without any scheduled maintenances. 829.12 km of the network are safe and intact and need no measurements.

Table 5-24. Length of pipelines for each scenario of model for 2035

Scenario	Replacement	Open Trench	Trenchless	water loss	Need nothing
Length (km)	30.70	1156.59	1453.53	1166.08	829.12

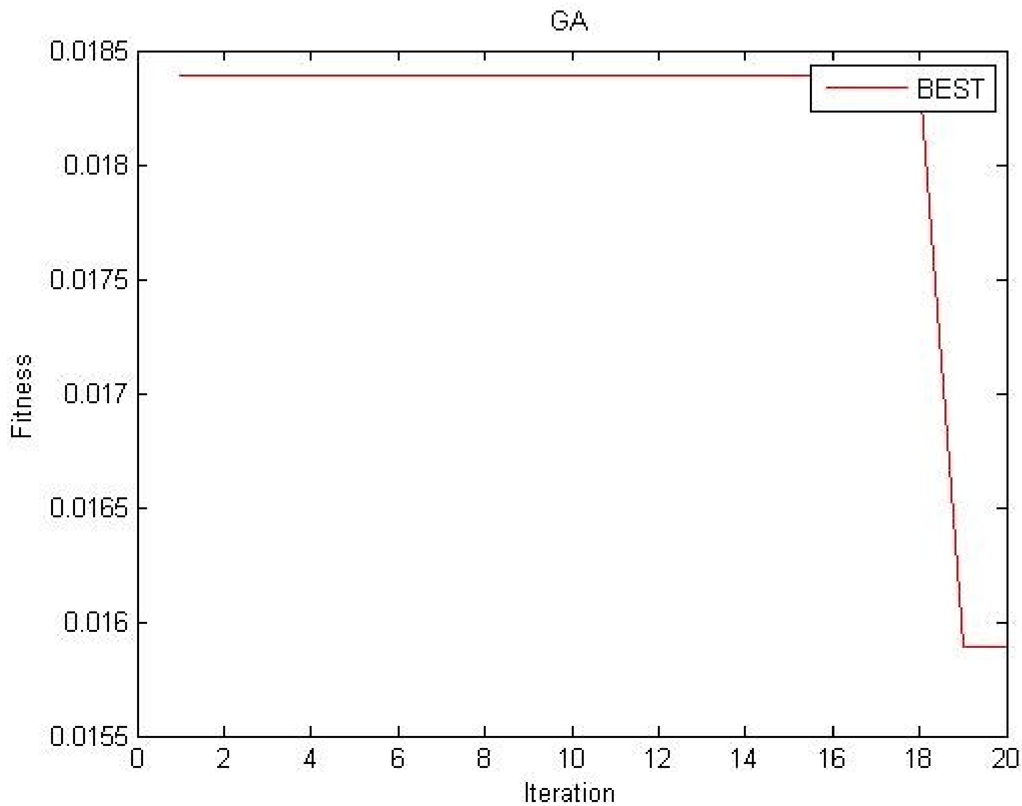


Figure 5-23. Fitness function for 2035

In the remaining useful life model, 768 pipelines have life expectancy less than 20 years. The proposed budget allocation model identifies 798 pipe segments which need replacement. This shows the competence of both models in predicting the pipes that need to be replaced. Table 5-25 displays the length of pipeline for each scenario in year 2040.

As can be seen from the table the length of pipe in urgent replacement is increasing in comparison to 2035.

Table 5-25. Length of pipelines for each scenario of model for 2040

Scenario	Replacement	Open Trench	Trenchless	water loss	Need nothing
Length (km)	64.17	1099.66	1253.51	1114.55	1104.12

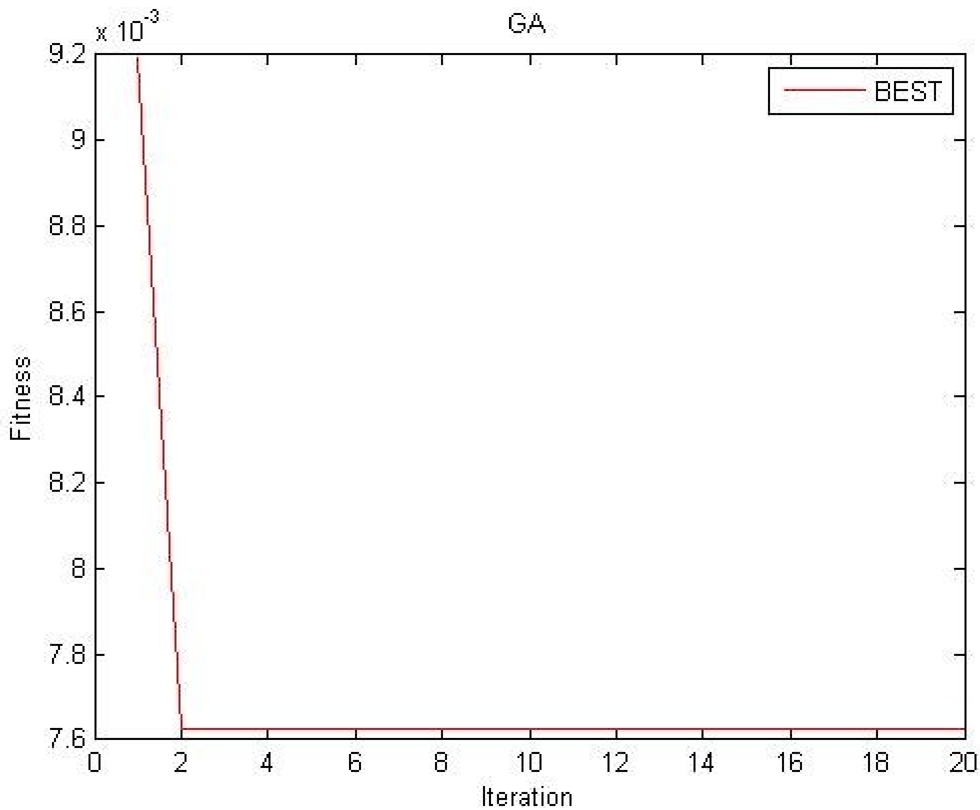


Figure 5-24. Fitness function for 2040

This model proved to be useful for future planning and scheduling of rehabilitation and replacement of pipe segment in water network with a constrained budget. However, the data should be updated to get the most accurate outcome. Table 5-26 shows the length of pipeline for each scenario considered in the model. It can be seen that the length of pipe in replacement class are increasing.

Table 5-26. Length of pipelines for each scenario of model for 2045

Scenario	Replacement	Open Trench	Trenchless	water loss	Need nothing
Length (km)	86.41	932.62	914.42	919.85	1782.71

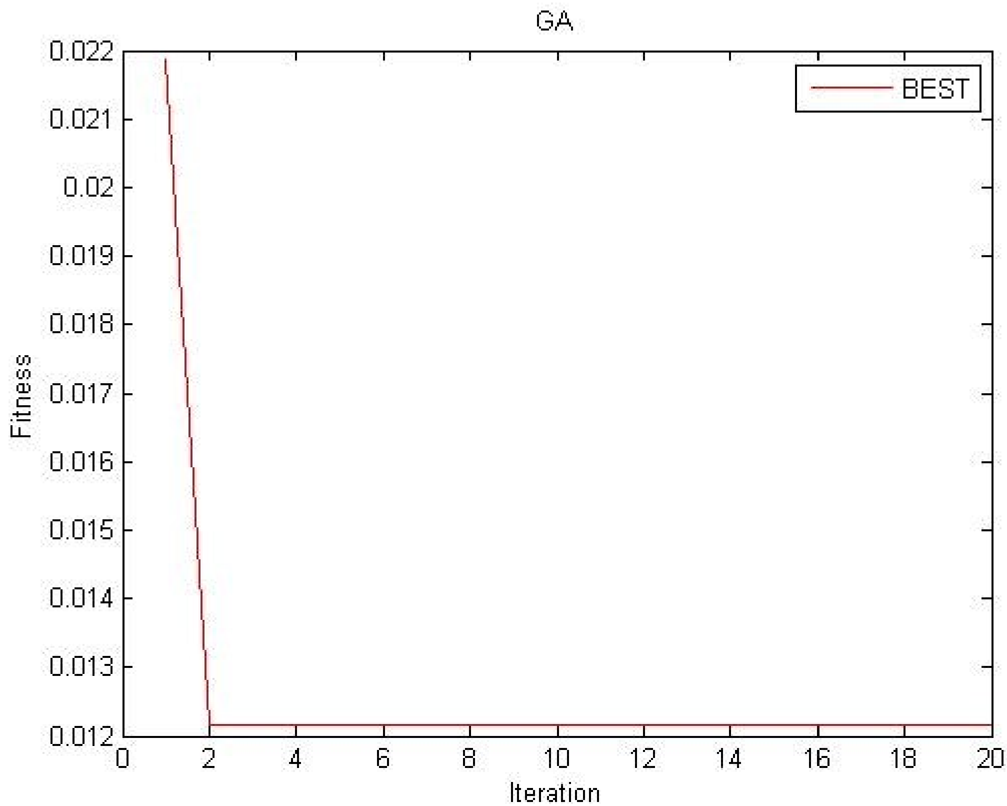


Figure 5-25. Fitness function for 2045

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

6.1. Summary and conclusions

As pipeline ages, considerable number of failures happen in pipelines. The associated direct and indirect costs of these failures have motivated scientists to figure out a way to prevent from disastrous failures and sudden shutdowns. A complete literature review of the existing researches highlights the limitation of developed models in various aspects such as emerging optimized scheduling plans in replacement and repair programs based on specifications of pipeline. Although the main subject has been studied extensively in the literature, most studies have focused merely on individual pipe segments instead of the whole network for generating a maintenance and replacement program. Moreover, the mentioned models rarely consider the long-term life and the physical specifications of the pipe to determine the performance of the segments and identify the pipeline that needs to undergo a measure.

The lack of competent models persuades this study to propose and establish an all-inclusive budget-based maintenance and replacement model for efficient management of water distribution networks through the life time of the pipe segments. The main model is developed in few separate sub-models. Delphi survey was applied in the first sub-model to find the factors of major importance. Much of the popularity of this method is based on the statement that "superiority of group over individual opinions and non-physical participation" (Gokhale, 2001). All in one, the Delphi judgments displays the group of experts' opinions rather than unquestionable fact. The selected causes could be classified into three categories of physical characteristics (pipe material, pipe installation, pipe age, pipe lining and coating, pipe wall thickness, dissimilar metals, and type of joints), environmental features (bedding soil type, backfill material, soil pH, seismic activity, and disturbance) and operational aspects (water pressure, O&M practices, leakage, and water pH). After that, Fuzzy Analytic Hierarchical Process (FAHP), Shannon Entropy and Integration of two methods are applied to determine the weight of importance of the selected factors considering the deterioration process. Results show that physical factors and operational factors are the most and least important category of factors respectively. Pipe specifications such as installation, age, material, utilizing dissimilar metals and lining and coating proved to have the most influence on pipeline deterioration through analysis which should be take into account while designing durable and reliable pipelines. The outcome of the first sub-model is an equation which predicts the condition index of different segments of the pipelines based on the factors selected in the Delphi survey and weighted by FAHP-Shannon Entropy method.

Having the breakage rate, pipe specifications and condition state in which pipe is in, the remaining useful life of the pipeline could be estimated as the second sub-model. Several different artificial neural network models with one or two hidden layer and different neurons of the hidden layer were implemented to forecast the remaining useful life of the pipelines in a distribution network. Levenberg–Marquardt, Bayesian Regularization and Scaled Conjugate Gradient algorithms are used to train, validate and test the ANN model in MATLAB 2014. Results show that Levenberg–Marquardt models are better for forecasting the remaining useful life and can predict remaining life of the pipeline approximately close to the expected results with coefficient of determination R^2 more than 98%. The model with 25 neurons in one hidden layer shows better performance and predictions that are more accurate. Based on the results, the ANN model shows robustness in prediction of remaining useful life.

Considering the declining residual life of the in-service pipelines and their future breakage rate, there will be no doubt that rehabilitation strategies are necessary to prevent from disastrous failures when a pipeline reaches the end of its useful life. Usually repair measurements are taken as reaction to detection of a leak which result in inefficient management of allocated funds. Therefore, careful computational analysis should be undertaken to utilize allocated constrained budget efficiently. The maintenance and rehabilitation sub-model presents a genetic algorithm optimization model to find the optimized scheduling for renewal and/or replacement of the water segments in a distribution network while considering the limited budget and relative cost of maintenance and replacement. Results proved that remaining useful life and future breakage rate are two significant parameters in arrangement of intervention plans. The main model has been applied to a case study and different optimized maintenance schedules are generated for different planning horizons. In order to ensure that there will be a situation where the balance in the budget is ended before the ended of fiscal year, the developed model can be applied at time intervals i.e. 3 months.

This research develops a comprehensive framework for optimized scheduling of maintenance and rehabilitation strategies of water distribution network based on the historical data. The key benefit of such models is that they can predict the future performance of the pipelines with or without inspection data. However, having the inspection data holds merit. These models can reduce cost of maintenance through optimized rehabilitation plans for a water distribution network over its life cycle.

6.2. Research contributions

The main contributions of this research are:

- An extensive review and study of previous performance models and leak detection techniques for water distribution networks; identifying their related advantages and limitations;
- Development of a robust performance assessment model for water infrastructure to predict pipeline condition utilizing a Delphi-based selection system and a FAHP-Shannon Entropy prioritizing scheme;
- Development of a prediction model utilizing artificial neural network to forecast remaining useful life of pipe segments in a network;
- Development of an integrated value-driven budget allocation model and utilizing it for scheduling rehabilitation and replacement strategies at network level.

6.3. Research limitations

This research has some limitations that can be summarized as:

- The two-tier inspection planning model has not been validated because inspection results were not available.
- The developed models are not fully automatic and need user to enter the outputs of one model as an input for the other model.
- The developed breakage model used in this study is developed to predict breakage rate of the city of Montréal and cannot be used for other regions.

- The neural network model does not output a mathematical equation for further analysis.
- Other infrastructures should be considered during maintenance of water pipelines such as roads and sewer networks. Therefore, corridor rehabilitation should be performed to benefit more from open trench activities. The model is valid only when road and sewer networks do not need any repair.
- The importance of the pipeline is not considered in the budget allocation model and all the pipe segments are treated equally due to the lack of data.

6.4. Future work and recommendations

This study aims to develop a value-driven budget allocation model to optimize the needed intervention plans based on the available budget. The proposed models in this study has achieved the suggested main objective and sub-objectives of section 1.2, however the existing study is able to be improved through some enhancements and extensions. Some recommendation for future works are:

- More questionnaires should be sent out to additional knowledgeable experts to validate the condition model.
- More parameters should be considered in calculating the condition index to boost the precision of the model in forecasting the condition of the pipe.
- Other training algorithm should be utilized to find the most accurate computing technique for future forecasting of remaining useful life.
- It is recommended to apply a breakage rate which is more generalized and can be used in all location to prevent model from being site-specific

- Other mathematical techniques should accompany neural network model to estimate a single mathematical equation for future rehabilitation planning and replacement scheduling of municipality of Montréal.
- It is better to consider more parameters for maintenance and replacement model as supplementary to remaining useful life and breakage rate to enhance the developed model with more inputs.
- It is recommended to address the location of the pipe segment such as residential area, industrial area, downtown, suburb, etc. in the budget allocation model to prioritize the segments based on their significance as well.
- The developed models should be automated together as a single input entry model to become more user friendly and applicable in municipalities.
- It's recommended to perform inspection every few years after installation of the segment to validate and modify model with collected inspection data. As a result, the forecasted future breakage rate can be checked with the data gathered from inspection results.
- It's more rewarding if different amount of money could be considered for minor and major rehabilitation and water loss based on the length and diameter of the pipe segment.

BIBLIOGRAPHY

Achim, D., Ghotb, F. and McManus, K. J. (2007). “Prediction of Water Pipe Asset Life Using Neural Networks”. Journal of Infrastructure Systems, 13(1), 26-30.

Al-Barqawi, H., and Zayed, T. (2006). "Condition rating model for underground infrastructure sustainable water mains". J.Perform.Constr.Facil., 20(2), 126-135.

Al-Barqawi, H., and Zayed, T. (2008). "Infrastructure management: integrated AHP/ANN model to evaluate municipal water mains performance". J Infrastruct Syst, 14(4), 305-318.

Alvisi, S., & Franchini, M. (2006). Near-optimal rehabilitation scheduling of water distribution systems based on a multi-objective genetic algorithm. Civil Engineering and Environmental Systems, 23(3), 143-160.

Amaitik, N. M., & Amaitik, S. M. (2008). “Development of PCCP wire breaks prediction model using artificial neural networks”. International Pipelines Conference, ASCE, Atlanta, 1–11.

AWWSC. (2002) “Deteriorating Buried Infrastructure Management Challenges and Strategies”. American Water Works Service Company Inc., Denver, CO.

Babovic, V., Draccourt, J., Keijzer, M., and Friss Hansen, P. (2002). "A data mining approach to modelling of water supply assets." Urban Water, 4(4), 401-414.

Bach, N. L., Fujiwara, O., & Luong, H. T. (2000). Optimal fund assignment and allocation models for pipe repair maintenance in leaky water distribution networks. Water Resources Research, 36(5), 1315-1324.

Baxter, C. W., Stanley, S. J., Zhang, Q., & Smith, D. W. (2002). “Developing artificial neural network models of water treatment processes: a guide for utilities”. Journal of Environmental Engineering and Science, 1(3), 201-211.

Berardi, L., Kapelan, Z., Giustolisi, O., and Savic, D. (2008). "Development of pipe deterioration models for water distribution systems using EPR." J.Hydroinf., 10(2), 113-126.

Burn, S., Davis, P., and Gould, S. (2009). "Risk Analysis for Pipeline Assets: The Use of Models for Failure Prediction in Plastics Pipelines". Springer, 183-204.

Canadian Infrastructure report card, 2016.

Chang, D. (1996). "Applications of the extent analysis method on fuzzy AHP". European journal of operational research 95 (3): 649-655.

Chen, C. (2000). "Extensions of the TOPSIS for group decision-making under fuzzy environment." Fuzzy Sets Syst., 114(1), 1-9.

Cherqui, F., Werey, C., Ibrahim, M., & Le Gauffre, P. (2008). "CCTV inspection of sewer segments: calibration of performance indicators based on experts' opinions". 11th International Conference on Urban Drainage, Edinburg, Scotland.

Christodoulou, S., Aslani, P., and Vanrenterghem, A. (2003). "A risk analysis framework for evaluating structural degradation of water mains in urban settings, using neurofuzzy systems and statistical modeling techniques". World Water & Environmental Resources Congress, ASCE, Philadelphia, 1–9.

Costello, S. B., Chapman, D. N., Rogers, C. D. F., and Metje, N. (2007). "Underground asset location and condition assessment technologies". Tunnel. Underground Space Technol., 22(5–6), 524-542.

Davis, P., and Marlow, D. (2008). "Quantifying economic lifetime for asset management of large diameter pipelines." American Water Works Association, 100(7), 110-119.

Davis, P., Burn, S., and Gould, S. (2008). "Fracture prediction in tough polyethylene pipes using measured craze strength". Polymer Engineering & Science, 48(5), 843-852.

Davis, P., Burn, S., Cardy, M., Gould, S., Sadler, P., and Tjandraatmadja, G. (2007). “Long-Term Performance Prediction for PE Pipes”. AWWA Research Foundation, Denver.

Davis, P., Burn, S., Moglia, M., and Gould, S. (2007). "A physical probabilistic model to predict failure rates in buried PVC pipelines". Reliab.Eng.Syst.Saf., 92(9), 1258-1266.

Davis, P., De Silva, D., Marlow, D., Moglia, M., Gould, S., and Burn, S. (2008). "Failure prediction and optimal scheduling of replacements in asbestos cement water pipes." Aqua-Journal of Water Supply, 57(4), 239-252.

De Silva, D., Moglia, M., Davis, P., & Burn, S. (2006). “Condition assessment to estimate failure rates in buried metallic pipelines”. Journal of Water Supply: Research and Technology-Aqua, 55(3), 179-191.

Deb, A. K. (2002). “Prioritizing water main replacement and rehabilitation”. American Water Works Association, Denver, CO.

Dehghan, A., McManus, K. J., and Gad, E. F. (2008). "Probabilistic failure prediction for deteriorating pipelines: Nonparametric approach". J.Perform.Constr.Facil., 22(1), 45-53.

Dehghan, A., McManus, K. J., and Gad, E. F. (2008). "Statistical analysis of structural failures of water pipes". Proceedings of the ICE-Water Management, 161(4), 207-214.

Fahmy, M., and Moselhi, O. (2010). "Automated Detection and Location of Leaks in Water Mains Using Infrared Photography". J.Perform.Constr.Facil., 24(3), 242-248.

Fares, H. A. (2008). “Evaluating the risk of water main failure using a hierarchical fuzzy expert system”, PhD dissertation, Department of building, civil and environmental engineering, Concordia University.

Fares, H., and Zayed, T. (2010). "Hierarchical fuzzy expert system for risk of failure of water mains." Journal of Pipeline Systems Engineering and Practice, 1(1), 53-62.

Farshad, M. (2004). "Two new criteria for the service life prediction of plastics pipes". Polym.Test., 23(8), 967-972.

Gadala, I. M., Wahab, M. A., & Alfantazi, A. (2016). "Numerical simulations of soil physicochemistry and aeration influences on the external corrosion and Cathodic protection design of buried pipeline steels". Materials & Design, 97, 287-299.

Gary, J. E., & Heiko, A. (2015). "The future of foresight professionals: Results from a global Delphi study". Futures, 71, 132-145.

Geem, Z. W., Tseng, C., Kim, J., and Bae, C. (2007). "Trenchless water pipe condition assessment using artificial neural network". Pipelines, ASCE, Reston, VA, 1–9.

Ghazali, M. F., Beck, S. B. M., Shucksmith, J. D., Boxall, J. B., & Staszewski, W. J. (2012). "Comparative study of instantaneous frequency based methods for leak detection in pipeline networks". Mechanical Systems and Signal Processing, 29, 187-200.

Giustolisi, O., Laucelli, D., & Savic†, D. A. (2006). "Development of rehabilitation plans for water mains replacement considering risk and cost-benefit assessment". Civil Engineering and Environmental Systems, 23(3), 175-190.

Gokhale, A. A. (2001). "Environmental initiative prioritization with a Delphi approach: a case study". Environmental management, 28(2), 187-193.

Grigg, N. (2006). "Condition Assessment of Water Distribution Pipes." J Infrastruct Syst, 12(3), 147-153.

Hao, T., Rogers, C. D. F., Metje, N., Chapman, D. N., Muggleton, J. M., Foo, K. Y., Wang, P., Pennock, S. R., Atkins, P. R., Swingler, S. G., Parker, J., Costello, S. B., Burrow, M. P. N., Anspach, J. H., Armitage, R. J., Cohn, A. G., Goddard, K., Lewin, P. L., Orlando, G., Redfern, M. A., Royal, A. C. D., and Saul, A. J. (2012). "Condition assessment of the buried utility service infrastructure." Tunnel.Underground Space Technol., 28(0), 331-344.

Hasson, F., Keeney, S., and McKenna, H. (2000). "Research guidelines for the Delphi survey technique." J.Adv.Nurs., 32(4), 1008-1015.

Haupt, R. L., & Haupt, S. E. (2004). “Practical genetic algorithms”. John Wiley & Sons.

Jaganathan, A. P., Allouche, E., & Simicevic, N. (2010). “Numerical modeling and experimental evaluation of a time domain UWB technique for soil void detection. Tunnelling and Underground Space Technology, 25(6), 652-659.

Jia, C., Wei, L., Wang, H., & Yang, J. (2015). “A Hybrid Model Based on Wavelet Decomposition-Reconstruction in Track Irregularity State Forecasting”. Mathematical Problems in Engineering, 10.1155/2015/548720.

Karimian, S. F. (2015). “Failure rate prediction model of water distribution networks”, Masters dissertation, Department of building, civil and environmental engineering, Concordia University.

Kim, J., Bae, C., Woo, H., Kim, J., & Hong, S. (2007). “Assessment of residual tensile strength on cast iron pipes”. In The ASCE International Conference on Pipeline Engineering and Construction, Boston, USA.

Kleiner, Y., & Rajani, B. (2008). “Prioritizing individual water mains for renewal”. World Environmental and Water Resources Congress, 1-10.

Kleiner, Y., Adams, B. J., & Rogers, J. S. (1998). Selection and scheduling of rehabilitation alternatives for water distribution systems. Water resources research, 34(8), 2053-2061.

Kleiner, Y., and Rajani, B. (1999). "Using limited data to assess future needs". Journal of American Water Works Association, 91(7), 47-61.

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

Kleiner, Y., Rajani, B. B., and Sadiq, R. (2005). “Risk management of large-diameter water transmission mains”, AWWA Research Foundation and American Water Works Association.

Laarhoven and Pedrycz (1983), van Laarhoven, P. J. M., & Pedrycz, W. (1983). “A fuzzy extension of Saaty’s priority theory”. Fuzzy Sets and Systems, 11, 229–241.

Laucelli, D., Berardi, L., & Giustolisi, O. (2012). “Assessing climate change and asset deterioration impacts on water distribution networks: demand-driven or pressure-driven network modeling?” Environmental Modelling & Software, 37, 206-216.

Lawrence, J. (1994). “Introduction to neural networks. Design, theory and applications”, California Scientific Software Press, Nevada City, CA.

Le Gat, Y., and Eisenbeis, P. (2000). "Using maintenance records to forecast failures in water networks." Urban Water, 2(3), 173-181.

Linstone, H. A., and Turoff, M. (1975). “The Delphi method: Techniques and applications”. Addison-Wesley Reading, MA.

Litwin, M. S. (1995). “How to measure survey reliability and validity? Vol. 7”, Sage Publications.

Liu, Z., and Kleiner, Y. (2013). "State of the art review of inspection technologies for condition assessment of water pipes". Measurement, 46(1), 1-15.

Liu, Z., Kleiner, Y., Rajani, B., Wang, L., & Condit, W. (2012). “Condition Assessment Technologies for Water Transmission and Distribution Systems”. United States Environmental Protection Agency (USEPA), Washington DC.

Loganathan, G. V., Park, S., and Sherali, H. D. (2002). "Threshold break rate for pipeline replacement in water distribution systems". J.Water Resour.Plann.Manage., 128(4), 271-279.

Lotfi, F. H., and Fallahnejad, R. (2010). "Imprecise Shannon's entropy and multi attribute decision making." Entropy, 12(1), 53-62.

Lu, J. P., Davis, P., and Burn, L. S. (2003). "Lifetime prediction for ABS pipes subjected to combined pressure and deflection loading". Polymer Engineering & Science, 43(2), 444-462.

Mack, N. C. (2011). "A Research Study Using the Delphi Method to Define Essential Competencies for a High School Game Art and Design Course Framework at the National Level". Doctoral dissertation, North Carolina State University, United States.

Mailhot, A., Poulin, A., & Villeneuve, J. P. (2003). Optimal replacement of water pipes. Water resources research, 39(5).

Makropoulos, C. K., and Butler, D. (2005). "A neuro-fuzzy spatial decision support system for pipe replacement prioritization". Urban Water Journal, 2(3), 141-150.

McDonald, S., & Makar, J. (1996). "Assessment of the Hydroscope 201 TM Condition Index Evaluation of Gray Cast-Iron Pipe from Gatineau, Quebec", NRC Report A-7015.3, National Research Council, Ottawa, Ontario.

Meijering, J., Kampen, J., and Tobi, H. (2013). "Quantifying the development of agreement among experts in Delphi studies". Technological Forecasting and Social Change, 80(8), 1607-1614.

Moglia, M., Burn, S., & Meddings, S. (2006). Decision support system for water pipeline renewal prioritisation. Decision Support Systems for Infrastructure Management 237-256.

Moglia, M., Davis, P., and Burn, S. (2008). "Strong exploration of a cast iron pipe failure model". Reliab.Eng.Syst.Saf., 93(6), 885-896.

Moselhi, O., Zayed, T., Khan, Z., & Salman, A. (2010). “Community-driven and reliability-based budget allocation for water networks”. Proceedings of the 2010 construction research congress: innovation for reshaping construction practice, 578-587.

Mutikanga, H. E., Sharma, S. K., and Vairavamoorthy, K. (2011). "Multi-criteria decision analysis: a strategic planning tool for water loss management." Water Resour.Manage., 25(14), 3947-3969.

Nafi, A., & Kleiner, Y. (2009). “Scheduling renewal of water pipes while considering adjacency of infrastructure works and economies of scale”. Journal of water resources planning and management, 136(5), 519-530.

Najjaran, H., Rajani, B., and Sadiq, R. (2004). "A fuzzy expert system for deterioration modeling of buried metallic pipes". IEEE, 373-378.

Najjaran, H., Sadiq, R., and Rajani, B. (2006). "Fuzzy expert system to assess corrosion of cast/ductile iron pipes from backfill properties". Computer Aided Civil and Infrastructure Engineering, 21(1), 67-77.

National Guide to Sustainable, Municipal Infrastructure. (2003). “Deterioration and Inspection of Water Distribution Systems: A Best Practice”. National Guide to Sustainable Municipal Infrastructure, Ottawa, Ontario.

Nazari, A., Rajeev, P., & Sanjayan, J. G. (2015). “Offshore pipeline performance evaluation by different artificial neural networks approaches”. Measurement, 76, 117-128.

Nepal, B., Yadav, O. P., and Murat, A. (2010). "A fuzzy-AHP approach to prioritization of CS attributes in target planning for automotive product development". Expert Syst.Appl., 37(10), 6775-6786.

Ngeru, J. (2012). "Multi-criteria decision analysis framework in the selection of an enterprise integration (EI) approach that best satisfies organizational requirements". Doctoral Dissertation, Morgan State University, Maryland, USA.

Okoli, C., and Pawlowski, S. D. (2004). "The Delphi method as a research tool: an example, design considerations and applications." Information & Management, 42(1), 15-29.

Ossai, C. I., Boswell, B., & Davies, I. J. (2015). “Pipeline failures in corrosive environments–A conceptual analysis of trends and effects”. Engineering Failure Analysis, 53, 36-58.

Ozer, M. (2007). ‘Reducing the demand uncertainties at the fuzzy-front-end of developing new online services”. Research Policy, 36(9), 1372-1387.

Park, S. W., and Loganathan, G. V. (2002). "Methodology for economically optimal replacement of pipes in water distribution systems: 2. Applications." KSCE Journal of Civil Engineering, 6(4), 545-550.

Pelletier, G., Mailhot, A., & Villeneuve, J. P. (2003). “Modeling water pipe breaks-three case studies”. Journal of Water Resources Planning and Management, 129(2), 115-123.

Pelletier, G., Mailhot, A., and Villeneuve, J. (2003). "Modeling water pipe breaks-three case studies." J.Water Resour.Plann.Manage., 129(2), 115-123.

Poulton, M., Le Gat, Y., and Bracmond, B. (2009). "The impact of pipe segment length on break predictions in water distribution systems." IWA Publishing, 419.

Powell, C. (2003). "The Delphi technique: myths and realities." J.Adv.Nurs., 41(4), 376-382.

Rajani, B., and Makar, J. (2000). "A methodology to estimate remaining service life of grey cast iron water mains." Canadian Journal of Civil Engineering, 27(6), 1259-1272.

Rajani, B., and Tesfamariam, S. (2005). "Estimating time to failure of ageing cast iron water mains under uncertainties." Water Management for the 21st Century, 1-7.

Rajani, B., and Tesfamariam, S. (2007). "Estimating time to failure of cast-iron water mains." Proceedings of the ICE-Water Management, 160(2), 83-88.

Rastum, J. (2000). "Statistical modelling of pipe failures in water networks".

Reid, N. (1988). "The Delphi technique: its contribution to the evaluation of professional practice." Professional Competence and Quality Assurance in the Caring Professions, 230-262.

Saaty, T. L. (1988). "What is the analytic hierarchy process?' Springer Berlin Heidelberg, 109-121.

Sachs, J., Badstübner, A., Bonitz, F., Eidner, M., Helbig, M., Herrmann, R. & Solas, H. (2008). "High resolution non-destructive testing in civil engineering by ultra-wideband pseudo-noise approaches". In IEEE International Conference on Ultra-Wideband, 137-140.

Sadiq, R., Rajani, B. and Kleiner. Y. 2004. "Fuzzy-Based Method to Evaluate Soil Corrosivity for Prediction of Water Main Deterioration". Journal of Infrastructure Systems 10 (4): 149-156.

Sægrov, S., Baptista, J. M., Conroy, P., Herz, R. K., LeGauffre, P., Moss, G. and Schiatti, M. (1999). "Rehabilitation of water networks: survey of research needs and on-going efforts". Urban Water, 1(1), 15-22.

Sarshar, Nima, Mahmoud R. Halfawy, and Jantira Hengmeechai. (2009). "Video processing techniques for assisted CCTV inspection and condition rating of sewers." Journal of Water Management Modeling, 129-147.

Savic, D. A. (2009). "The use of data-driven methodologies for prediction of water and wastewater asset failures". Springer, 181-190.

Sawhney, A., & Mund, A. (2002). “Adaptive probabilistic neural network-based crane type selection system”. Journal of construction engineering and management, 128(3), 265-273.

Sbarufatti, C., Corbetta, M., Manes, A., & Giglio, M. (2016). “Sequential Monte-Carlo sampling based on a committee of artificial neural networks for posterior state estimation and residual lifetime prediction”. International Journal of Fatigue, 83, 10-23.

Seica, M. V., & Packer, J. A. (2004). “Finite element evaluation of the remaining mechanical strength of deteriorated cast iron pipes”. Journal of engineering materials and technology, 126(1), 95-102.

Seica, M. V., and Packer, J. A. (2006). "Simplified numerical method to evaluate the mechanical strength of cast iron water pipes." J Infrastruct Syst, 12(1), 60-67.

Shannon, C. E. (2001). "A mathematical theory of communication". ACM sigmobile mobile computing and communications review, 5(1), 3-55.

Tesfamariam, S., Rajani, B., and Sadiq, R. (2006). "Possibilistic approach for consideration of uncertainties to estimate structural capacity of ageing cast iron water mains." Canadian Journal of Civil Engineering, 33(8), 1050-1064.

Vahidnia, M., Alesheikh, A., Alimohammadi, A., and Bassiri, A. (2008). "Fuzzy analytical hierarchy process in GIS application". The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 37(B2), 593-596.

Vanrenterghem-Raven, A., Hafskjold, S., Rostum, J., Laughter, G. and Simpson, P. (2007). “Planning and rehabilitation of the Las Vegas distribution network using CARE-W”, LESAM 2007, IWA and LNEX, Lisbon.

Von Der Gracht, Heiko A. (2012). "Consensus measurement in Delphi studies: review and implications for future quality assurance." Technological Forecasting and Social Change, 79(8), 1525-1536.

Wang, C., Niu, Z., Jia, H., and Zhang, H. (2010). "An assessment model of water pipe condition using Bayesian inference." Journal of Zhejiang University SCIENCE A, 11(7), 495-504.

Wang, Y. (2006). "Deterioration and condition rating analysis of water mains", Doctoral dissertation, Department of building, civil and environmental engineering, Concordia University.

Wang, Y., Zayed, T., and Moselhi, O. (2009). "Prediction models for annual break rates of water mains." J.Perform.Constr.Facil., 23(1), 47-54.

Watson, T., Christian, C., Mason, A., Smith, M., and Meyer, R. (2004). "Bayesian-based pipe failure model." J.Hydroinf., 6 259-264.

Wilson, J. W., Kaba, M., & Tian, G. Y. (2008). "New techniques for the quantification of defects through pulsed magnetic flux leakage". In Proceedings of 17th World Conference on Nondestructive Testing, Shanghai, China.

Wood, A., and Lence, B. J. (2009). "Using water main break data to improve asset management for small and medium utilities: district of maple ridge, BC." J Infrastruct Syst, 15(2), 111-119.

Xia, B. (2010). "The Selection of Design-build Operational Variations in the People's Republic of China Using Delphi Method and Fuzzy Set Theory". Ph.D. Hong Kong Polytechnic University (Hong Kong), Hong Kong.

Yang, M. D., Su, T. C., Pan, N. F., & Yang, Y. F. (2011). "Systematic image quality assessment for sewer inspection". Expert Systems with Applications, 38(3), 1766-1776.

Yeung, F. Y. (2007). "Developing a Partnering Performance Index (PPI) for construction projects---a fuzzy set theory approach". Ph.D dissertation, Hong Kong Polytechnic University, Hong Kong.

Yu, F., Fang, G., and Shen, R. (2014). "Study on comprehensive early warning of drinking water sources for the Gucheng Lake in China". Environmental Earth Sciences, 1-8.

Zadeh, L. A. (1965). “Fuzzy sets”. Information and control, 8(3), 338-353.

Zangenehmadar, Z., Moselhi, O., (2014). “study of leak detection technologies in water distribution networks”, Canadian Society of civil engineering annual conference (CSCE), Halifax, NS, Canada.

Zangenehmadar, Z., Moselhi, O., (2015) “Assessment of Remaining Useful Life of Pipelines Using Different Artificial Neural Networks Models”, Journal of Performance of Constructed Facilities, 10.1061/(ASCE)CF.1943-5509.0000886, 04016032.

Zangenehmadar, Z., Moselhi, O., (2015). “Application of FAHP and Shannon Entropy in Evaluating Criteria Significance in Pipeline Deterioration.” ICSC15, Vancouver, BC, Canada.

Zangenehmadar, Z., Moselhi, O., (2015). “Application of Infrared thermography in leak detection in water distribution techniques”, Inframation2015, Nashville, Tennessee, USA.

Zangenehmadar, Z., Moselhi, O., (2016). “Prioritizing deterioration factors in water pipelines using Delphi method”, Measurement 90, 491-499.

Zhou, Y., Vairavamoorthy, K., and Grimshaw, F. (2009). "Development of a Fuzzy based pipe condition assessment model using PROMETHEE". World Environmental and Water Resources Congress 2009, 1-10.

LIST OF NOTATIONS

A: Pipe Age

AC: Asbestos Cement

Ae_i: Attributes Effect

AHP: Analytical Hierarchy Process

ANN: Artificial Neural Network

ASCE: American Society of Civil Engineering

AWWSC: American Water Works Service Company

BEM: Broadband Electromagnetics

BM: Backfill Material

BR: Bayesian Regularization

BR: Breakage Rate

C: Condition

c: Propagation Velocity of Sound

CCTV: Closed-Circuit Television

CI: Cast Iron

CI: Condition Index

CI: Consistency Index

$C_i^{repair\ Major}$: Cost of Major Repair

$C_i^{repair\ Minor}$: Cost of Minor Repair

C_i^{social}: Social Cost of Pipe Breakage

$C_i^{water\ Loss}$: Cost of Water Loss

CR: Consistency Ratio

Cr_i: Cost Of Replacement

C_{total}: Total Cost

D: Diameter

D: Distance between Two Access Points.

D_i: Degree of Diversification

DI: Disturbance

DI: Ductile Iron

DM: Dissimilar Metals

E: Shannon's Entropy

EPR: Evolutionary Polynomial Regression

FAHP: Fuzzy Analytical Hierarchy Process

$F_{p:}$ Peak Frequency

FS: Factor of Safety

GA: Genetic Algorithm

GPIR: Ground Penetrating Imaging Radar

GPR: Ground Penetrating Radar

I: Pipe Installation

J: Type of Joints

$K_{i,T}$: Number Of Break For Each Pipe I

L: Length

L_1 & $L_{2:}$ Positions of The Leak Respect to The Access Points

LC: Pipe Lining and Coating

LE: Leakage

LM: Levenberg–Marquardt

M: Mobilization Cost

M: Pipe Material

MAE: Mean Absolute Error

MAPE: Mean Absolute Percentage Error

MFL: Magnetic Flux Leakage

MLP: Multi-Layer Perceptron Model

MLR: Multiple Linear Regression

MSE: Mean Square Error

N: Total Number of Possible Outcomes

O&M: Operation and Maintenance

O: O&M Practices

O_i: Output Value

P: Random Variable

P: Water Pressure

PCCP: Pre-Stressed Concrete Cylinder Pipe

PE: Polyethylene

P_i: Probability

PVC: Polyvinyl Chloride

RAE: Relative Absolute Error

RC: Reinforced Concrete

RFEC: Remote Field Eddy Current

RI: Random Inconsistency Index

RRSE: Root Relative Square Error

RUL: Remaining Useful Life

SA: Seismic Activity

SCG: Scaled Conjugate Gradient

SP: Soil pH

SS: Stainless Steel

ST: Bedding Soil Type

T: Pipe Wall Thickness

T: Thickness

T_i: Target Value

UWB: Ultra-Wideband

V: Wave Velocity

WDN: Water Distribution Network

$W_{i,J}$: Weight Of Parameter I Respect To Parameter J

W_i: Weight of Factors

W_i: Weight of Importance from FAHP

WIP: Wave Impedance Probe

WP: Water pH

Y_i: Weight of Importance from Entropy

Y_i: Weight of Sub-Factors

$T_{max:}$ Time Lag

APPENDICES

Appendix A: Coding

Appendix A1: Insert Data Function:

```
Function data=InsertData(k)

A=xlsread('input.xlsx','problem');

C=A(:,1:5);

A(:,1:5)=[];

K=repmat(A(:,k),1,5);K(:,[1 4])=1;

na=size(A,1);

Tar=82.3 *10^6;

TEL=1;

save data

data=load('data.mat');



end
```

Appendix A2: Mutation Function

```
function  mutpop=mutation(mutpop,pop,nmut,popsize,data)

for n=1:nmut



i1=randi([1 popsize]);



mutpop(n).x=ContinuseMutate(pop(i1).x,0.01,0,1);

mutpop(n)=fitness(mutpop(n),data);

end

end

function y=ContinuseMutate(x,mu,lb,ub)



    nVar=numel(x);



    nmu=ceil(mu*nVar);



    j=randsample(nVar,nmu);
```

```
    d=1*unifrnd(-1,1,size(x)).*(ub-lb);

    y=x;

    y(j)=x(j)+d(j);

    y=max(y,lb);

    y=min(y,ub);


end

function y=Swap(x)

    n=numel(x);


    i=randsample(n,2);

    i1=i(1);

    i2=i(2);

    y=x;

    y([i1 i2])=x([i2 i1]);


end

function y=Reversion(x)
```

```
    n=numel(x);

    i=randsample(n,2);
    i1=min(i);
    i2=max(i);

    y=x;
    y(i1:i2)=x(i2:-1:i1);

end


function
crosspop=crossover(crosspop,pop,ncross,data,popsize)

f=[pop.cost];
f=1./f;
f=f./sum(f);
f=cumsum(f);
```

```
for n=1:2:ncross

    i1=find(rand<=f,1,'first');

    i2=find(rand<=f,1,'first');

[crosspop(n).x,crosspop(n+1).x]=ContinuseCrossover(pop(i1).
x,pop(i2).x);

crosspop(n)=fitness(crosspop(n),data);

crosspop(n+1)=fitness(crosspop(n+1),data);

end

end

function [y1,y2]=ContinuseCrossover(x1,x2)
```

```
    R=rand(size(x1));

    y1=(R.*x1)+((1-R).*x2);
    y2=(R.*x2)+((1-R).*x1);

end

function [y1,y2]=SinglePointCrossover(x1,x2)

    nVar=numel(x1);

    c=randi([1 nVar-1]);
    y1=x1;
    y2=x2;

    y1(1:c)=x2(1:c);
    y2(1:c)=x1(1:c);
```

```
end
```

Appendix A3: Crossover Function

```
function [o1,o2]=TwoPointCrossover(x1,x2)

 nvar=numel(x1);

t1=randi([1 nvar-2]);
t2=randi([t1+1 nvar-1]);

p1=x1;
p2=x2;
o1=p1;
o2=p2;
o1(t1+1:t2)=p2(t1+1:t2);
o2(t1+1:t2)=p1(t1+1:t2);
```

```
end
```

Appendix A4: Fitness Function

```
function sol=fitness(sol,data)

load data

C=data.C;

K=data.K;



x0=sol.x;

x=ceil(x0*5);x(x==0)=1;

xx=full(ind2vec(x'))';

s=xx.*C.*K;

b=sum(s(:));

ch=b-Tar;

[~,ind]=sort(x0);

ind=ind';

i=ind(1);
```

```
if ch<0;else

    for i=ind
        e=sum(s(i,:));
        if e<=ch
            xx(i,:)=0;
            xx(i,5)=1;
            s=xx.*C.*K;
            b=sum(s(:));
            ch=b-Tar;
        else
            g=C(i,:).*K(i,:);
            a=find(g==ch);

            if isempty(a)

            else
                xx(i,:)=0;
```

```
                xx(i,a)=1;

                s=xx.*C.*K;

                b=sum(s(:));

                ch=b-Tar;

            end

        end

        if ch<=TEL;break;end


    end

end




fit=abs(ch);



sol.cost=fit;

sol.info.xx=xx;

sol.info.ch=ch;

sol.info.b=b;
```

```
end
```

Appendix A5: Genetic Algorithm code

```
clc

clear

close all

format shortG


%% parametres setting

k=1;

data=InsertData(k);

load data

nvar=na;


npop=10;     % number of population


pc=0.8;       % percent of crossover
```

```
ncross=2*round(npop*pc/2);  % number of crossover offspring


pm=1-pc;        %  percent of mutation

nmut=round(npop*pm);  % number of mutation offspring


maxiter=20;



%% initialization

tic

emp.x=[];

emp.cost=[];

emp.SCH=[];

emp.info=[];





pop=repmat(emp,npop,1);
```

```
for i=1:npop

pop(i).x=rand(na,1);

pop(i)=fitness(pop(i),data);

end


%% main loop

BEST=zeros(maxiter,1);


for iter=1:maxiter


    % crossover

    crosspop=repmat(emp,ncross,1);

     crosspop=crossover(crosspop,pop,ncross,data,npop);


     % mutation

     mutpop=repmat(emp,nmut,1);

     mutpop=mutation(mutpop,pop,nmut,npop,data);
```

```
      [pop]=[pop;crosspop;mutpop];

    [value,index]=sort([pop.cost]);
    pop=pop(index);
    gpop=pop(1);
    pop=pop(1:npop);

      NO=' Feasible';

      if any([gpop.SCH]>0)
          NO=' Infeasible';
      end

BEST(iter)=gpop.cost;

disp([' Iter = ' num2str(iter)  ' BEST = '
num2str(BEST(iter)) NO])
```

```
end

%% results

disp([ ' Best SUM = '  num2str(gpop.info.b)])
disp([ ' Time = '  num2str(toc)])
xlswrite('out.xlsx',gpop.info.xx,1,'d5');
figure(1)
plot(BEST,'r')
xlabel('Iteration')
ylabel('Fitness')
legend('BEST')
title('GA')
```

Appendix A6: Neural Network coding

```
% Solve an Input-Output Fitting problem with a Neural
Network
% Script generated by Neural Fitting app
```

```
% Created Mon Dec 07 18:45:15 EST 2015
%
% This script assumes these variables are defined:
%
%   condition - input data.
%   RUL - target data.

x = condition';
t = RUL';

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging
problems.
% 'trainscg' uses less memory. NFTOOL falls back to this in
low memory situations.
trainFcn = 'trainlm';  % Levenberg-Marquardt
```

```
% Create a Fitting Network

hiddenLayerSize = 30;

net = fitnet(hiddenLayerSize,trainFcn);


% Choose Input and Output Pre/Post-Processing Functions

% For a list of all processing functions type: help
nnprocess

net.input.processFcns = {'removeconstantrows','mapminmax'};

net.output.processFcns =
{'removeconstantrows','mapminmax'};


% Setup Division of Data for Training, Validation, Testing

% For a list of all data division functions type: help
nndivide

net.divideFcn = 'dividerand';  % Divide data randomly

net.divideMode = 'sample';  % Divide up every sample

net.divideParam.trainRatio = 70/100;

net.divideParam.valRatio = 15/100;

net.divideParam.testRatio = 15/100;
```

```
% Choose a Performance Function
% For a list of all performance functions type: help
nnperformance
net.performFcn = 'mse';  % Mean squared error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns =
{'plotperform','plottrainstate','ploterrhist', ...
  'plotregression', 'plotfit'};

% Train the Network
[net,tr] = train(net,x,t);

% Test the Network
y = net(x);
e = gsubtract(t,y);
performance = perform(net,t,y)
```

```
% Recalculate Training, Validation and Test Performance

trainTargets = t .* tr.trainMask{1};

valTargets = t  .* tr.valMask{1};

testTargets = t  .* tr.testMask{1};

trainPerformance = perform(net,trainTargets,y)

valPerformance = perform(net,valTargets,y)

testPerformance = perform(net,testTargets,y)


% View the Network

view(net)


% Plots

% Uncomment these lines to enable various plots.

%figure, plotperform(tr)

%figure, plottrainstate(tr)

%figure, plotfit(net,x,t)

%figure, plotregression(t,y)
```

```
%figure, ploterrhist(e)


% Deployment
% Change the (false) values to (true) to enable the
following code blocks.
if (false)
  % Generate MATLAB function for neural network for
application deployment
  % in MATLAB scripts or with MATLAB Compiler and Builder
tools, or simply
  % to examine the calculations your trained neural network
performs.
  genFunction(net,'myNeuralNetworkFunction');
  y = myNeuralNetworkFunction(x);
end
if (false)
  % Generate a matrix-only MATLAB function for neural
network code
  % generation with MATLAB Coder tools.
```

```
genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes
');
  y = myNeuralNetworkFunction(x);
end
if (false)
  % Generate a Simulink diagram for simulation or
deployment with.
  % Simulink Coder tools.
  gensim(net);
end
```