Integrated Multiple-Sensor Methodology for Condition Assessment of Water Mains

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ABSTRACT

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Considerable capital investment has been made in civil infrastructure systems across the globe including water mains. Currently, existing failure detection and location methods do not allow for quick reaction to failures. In addition, no unified standards are followed in condition assessment of water mains. Moreover, the decision by which water mains are inspected is currently carried out based on approximation and experience of decision-makers, which might be limited and may lead to overlooking suitable evaluation methods that might save time, effort and cost.

This research presents a methodology that contributes to different phases in the asset management of water mains. It enhances current practice in condition assessment of water mains and assists in setting up rehabilitation priorities.

The methodology implemented is based on intensive literature review, evaluation of current methods, field investigation and experiments, and interviews with experts. The methodology considered augments two approaches currently used in condition assessment of water mains, which are proactive and reactive methods.

The developed methodology calls for designing a new decision support system (DSS) for selection of most suitable non-destructive evaluation (NDE) method

(s). It consists of two components: 1) A Database management system (DBMS), and 2) an evaluation and ranking module (ERM).

These NDE methods are used for either detecting suspected leaks or measuring pipe wall thickness, the latter is employed to predict remaining service life of pipe being considered.

In case of suspected leaks, this study presents a newly designed automated system for detection of water leaks in underground pipelines and identifying their respective locations. The development of this system is based on using Thermography infrared (IR) camera in order to detect thermal contrast at the pavement surface due to water leaks at the most suitable time. The data obtained is analyzed in order to establish the relationship between the detected leakage area and the approximate location of leak. Prototype software developed in Visual C# environment is implemented in order to determine the location of leaks automatically.

Two deterioration models were designed and developed for estimating remaining useful life of water mains, and predicting annual breakage rate of water mains. The development of the two models is based on the analysis of real data collected from 16 municipalities in Canada and the US. The two models were developed considering two approaches, multiple regression analysis and Artificial Neural Networks (ANNs) based on the most suitable subsets of selected factors. The final model was selected due to its reliability and better performance in comparison to other models.

The outputs of the deterioration models developed in this research were used, in addition to other deterioration factors that were not considered in existing models in order to develop a Decision Support System (DSS) for generating condition rating scale of water main being considered, and for prioritizing rehabilitation/ maintenance actions. The system is hierarchal in structure, and the condition-rating index is generated using Multi Attributes Utility Theory (MAUT). System validation was carried out by comparing its outcome with real case studies.

A prototype software application of the model presented in this research is implemented as a proof of concept to demonstrate the capabilities and essential features of the developed models.

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NOMENACLARTORS

A : Pipe Age

ANN : Artificial Neural Networks

B : Burial depth of pipe (m)

BPNN : back propagation neural network

C : Corrosion depth (mm)

CI : Cast Iron

C_p: Mallows Value

CR : Consistency Ratio

D : Pipe diameter (mm)

GRNN: General Regression Neural Networks

IR: Infrared

K: Soil aeration index

M: Type of pipe manufacture (pit/spun)

MLP: Multi-Layers Perceptron

pH:: Soil Acidity/Alkalinity

R: Ring rupture modulus

R^2: Coefficient of multiple determination

SF: Load safety factor

t: pipe wall thickness

TT: Trenchless Technology

p: pipe internal pressure

w: External load (e.g. traffic load)

ρ: Soil resistivity

CHAPTER 1

INTRODUCTION

1.1 Research Motive

The infrastructure of Canada is aging rapidly. Almost 60 percent of the $1.6-trillion network of roads, bridges, sewers and water mains, and other components are more than 50 years old (National Guide 2003). Some (30%) is more than 80 years old and nearing the end of its service life. In addition to the need for repairs or replacement, there are many other pressures on municipalities, such as the increase in population and the consequent need for more services, the need to adopt new and higher standards for environmental protection and the need to apply new and better technology. The Canadian Water and Wastewater Association (CWWA) completed a study in 1997 to estimate the investment needs in water and wastewater infrastructure over the period 1997-2012. This study indicated that there were more than 112,000 kilometers of water mains in Canada with an estimated replacement cost of $34 billion. Furthermore, this study revealed that $12.5 billion would have to be invested over this 15-year period to replace existing (deteriorated) water mains and to construct new mains to service the projected growth. Furthermore, it is reported that the cost of replacing all water mains in the United States would run to US $348 billion, while upgrading would cost US $77 billion over the next 20 years (Baer 1998). Based on the magnitude of this projected need, it is apparent that available funds will need to be targeted as effectively as possible. In order to attain this target, effective planning for the renewal of water distribution systems requires accurate quantification of the structural deterioration of water mains (Makar and Rajani 2000). It should be noted that condition assessment of water mains poses a major challenge for most municipalities, as they embark on providing quality service and preserving their infrastructure assets.

Currently, there are many types of water mains including but not limited to cast iron, ductile iron, HPVC, PCCP, etc., surrounded by different soil and underground water conditions. Therefore, water mains have different failure modes and require different rehabilitation methods. In addition, each type of pipe requires an efficient method to evaluate its condition. Consequently, there is a need for the development of a comprehensive model and computer-aided tools to assist decision makers in management of water utilities.

This research presents a methodology that contributes to different phases in the asset management of water mains. It facilitates the decision process in condition assessment of water mains, and can improve reliability, safety and efficiency of the water networks. In addition, it makes a significant contribution to the body of knowledge and presents the knowledge and experience of experts that can be beneficial to junior engineers and the decision makers in water utilities.

1.2 Current Practice

Pipeline damage in water distribution and transmission systems is difficult to inspect due to their location below the surface of the ground. Even where the pipe is large enough to be entered by a human inspector, most of the damage to the pipe occurs on its outside surface (for metallic pipes) or in the centre of the pipe wall (for pre-stressed concrete pipes). This difficulty has led water utilities to rely on techniques such as breakage records, leak detection, and water audits to determine the health of their systems (Makar and Chagnon 1999). Appendixes A-1 and A-2 describe various types of non-destructive inspection methods and various types of water mains commonly used in current practice, respectively. However, these direct inspection methods are expensive and not available to most water utilities; another alternative is employing one of the developed condition rating models. Employing these models is considered an effective and inexpensive alternative. However, a previous study, involving 45 water utilities from North America and UK, showed that only 30% of water utilities applied models to assist them in planning water main renewal. This low rate indicates that research efforts are often not interpreted into operational tools and further investigation is required (Kliener *et al.* 2001). On the other hand, a typical protection, rehabilitation or replacement process of underground water main pipes usually starts with collecting information about the project requirements and (or) constraints (i.e., diameter, type of defect, and cost). This set of information is then processed to select the most suitable rehabilitation method(s) that satisfies the requirements of the project and the decision-maker. Currently, the above-mentioned selection process is carried out based on decision-maker's experience and his/her knowledge, which might be limited and without computer-assisted tools.

1.3 Limitations of Current Practice

While the inspection methods have been shown to be very useful in prioritizing repairs and replacements of water mains, they have the disadvantage of being reactive in nature (Makar and Chagnon 1999). In each case, problems with the water system become apparent only after the pipes have failed in some manner. As a result, water utilities repair damage rather than prevent it (Makar 2000). On the other hand the decisions by which water mains are inspected, protected, rehabilitated, or replaced is currently carried out by municipal engineers or technicians, who are not necessarily experts. Moreover, the evaluation process is carried out without comprehensive computer-assisted tools, thereby the decision is most likely time consuming, might be expensive, possibly increase safety hazard and vulnerable to human errors. Furthermore, using a single evaluation method provides users with partial assessment of their water mains, while, integration of different evaluation methods into a framework would provide users with an efficient condition assessment of their water mains. For instance, water audits provide broad information about the condition of a wide area of a water distribution network, without determining the location of leaks, whereas acoustic leak detection methods find approximate location of leak in already broken or damaged pipes. On the other hand, the remote field effect can inspect pipes to find damage before they fail. It is apparent that the selection of most suitable inspection method is a challenging task that requires expertise and knowledgeable engineers. Furthermore, the condition rating models currently used in North America to manage rehabilitation planning in water utilities are without unified standards (Al-Barqawi and Zayed 2006). Nowadays, only approximations and expert opinions, which are not available in most municipalities are used to determine the condition rating of water mains.

1.4 Research Objectives

This research aims to develop a methodology that adds to the body of knowledge and enhances current practice in condition assessment of water mains. In addition, it provides a framework to municipal engineers and researchers that assists in evaluation and prioritizing maintenance/ rehabilitation actions for existing water mains. In order to fulfill this main objective, the following sub-objectives were identified:

1. Study current practice, related literature, and a wide range of Non-Destructive (ND) inspection methods for water mains.
2. Develop a methodology to assist in selection of the most suitable inspection method(s)
3. Design effective models that augment and enhance current practice for detection of water leaks in water mains and determine their respective locations, prediction of annual failure rates of cast iron (CI) water mains, forecasting of remaining useful life of CI water mains, condition rating

scale for CI water mains and recommending maintenance/rehabilitation actions.

4. Implement the developed methodology in a prototype software system as a proof of concept, which could demonstrate the capabilities and essential features of the developed methodology.

1.5 Research Methodology

In order to meet the aforementioned objectives, the following procedure was carried out:

1. Intensive literature review.
2. Experts' Interviews.
3. Data Collection and analysis.
4. Field Investigation and Experimental Works.
5. Methodology Development.
6. Results Testing and Validation
7. Implementing the Developed Methodology in a Prototype Software System

A detail description of the methodology can be found in Chapter 3.

1.6 Thesis Organization

Chapter Two presents a literature review of the structural failure of water mains and current practice of condition assessment of water mains. It demonstrates various Non-Destructive (ND) tools utilized in evaluation of water mains and their importance and limitations. Moreover, it explains the relevant research done in this area and their limitation(s). It also demonstrates the use and importance of ANNs and multiple regression analysis as powerful tools in modeling prediction tasks. In addition, it describes the principles of thermography and its use in detecting thermal changes in soil due to leaks in underground water mains, discusses theories of heat and moisture transfer in soil, and heat balance at the pavement surface. A brief summary on protection and rehabilitation of cast iron water mains is mentioned as well.

Chapter Three presents the proposed methodology and describes its structure and the interrelation between its main components. It describes concepts, procedures followed in implementing and developing new models and sub-systems that can be used for condition assessment and prioritizing rehabilitation actions of water mains.

Chapters Four through Eight presents newly designed and developed models and sub-systems. It describes the basis on which each model's variables are selected; data collection and analysis, applying data to existing models to identify their limitations, field investigation carried out, and results obtained. It also describes the advantages and limitations, in addition to validation of these models and sub-systems.

Chapter Nine provides a summary of the contributions of the current research, limitations of models developed in this research, concluding remarks, and recommendations for future research

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

As water infrastructure assets are getting older, the number of pipe failures is increasing. Therefore, an efficient failure management strategy becomes important. In this thesis, different aspects of failure management in urban water supply systems are discussed. For efficient failure management two types of failure management strategies can be applied: proactive asset condition assessment to prevent a failure and reactive failure detection and location to minimize the reaction time and the associated loss due to failure. Currently available asset condition assessment techniques cannot be extensively applied to inspect water supply systems due to high cost and extensive time required. Therefore, there is a need for systematic inspection and monitoring techniques.

Due to the large number of methods associated with emerging new technologies in the evaluation and rehabilitation of water mains, selecting most suitable method of inspection and/or rehabilitation can be a challenging task. Studies undertaken by Shehab-Eldeen and Moselhi (2001); Marzouk and Moselhi (2003); Al-Aghbar and Moselhi (2005) have revealed that, a computerized decision support system software application is very essential to assist decision makers to remotely detect and quickly respond to asset failures. In addition, current methods of selection in this environment may also suffer from the limited knowledge and/or experience of the decision-makers in water utilities, and could result in overlooking some of the suitable methods that could do the job in less time and at less cost.

2.2 Structural Failure of Water Mains

The structural deterioration of water mains and their subsequent failure are complex processes. Many factors can affect the rate of the deterioration of water distribution systems and lead to their failure. These factors can be physical, external environmental, or operational. (Appendix A- 3) summarizes some of these factors and explains how they affect the deterioration of water mains. Previous work carried out by researchers such as Makar and Chagnon (1999); Kleiner and Rajani (1999) and (2000), ;Kroon (2001) have studied the degradation of metallic and PCCP water mains, which represent over 70% of the total network of water mains in North America (Rajani et al. 2000; Makar 2000; Makar and Kleiner 2000; National Guide 2003). Their studies revealed that corrosion is largely responsible for both metallic pipes and PCCP failure. Kroon (2001) and Waters (2001) described pitting corrosion, which is initiated by a localized anodic point on the metal surface. The penetration of the metal continues at this same point because a relatively large area around the pit is cathodic to the pit itself. Pitting corrosion is commonly encountered at pinholes or flaws in dielectric coating systems. For steel and stainless steel, chloride ions are well known as a cause of pitting attacks. In such cases, either a corrosion pit in the pipe wall grows from the inside or the outside surface until the pipe has been completely penetrated, allowing water leakage from the pipe.

Water mains typically break when the extent of corrosion (or degradation) is such that the main is no longer able to withstand the forces acting on it. Figure 2-1 illustrates the most common types of water main breaks. Appendix A- 4 summarizes the structural failure modes for each of the common water main materials.

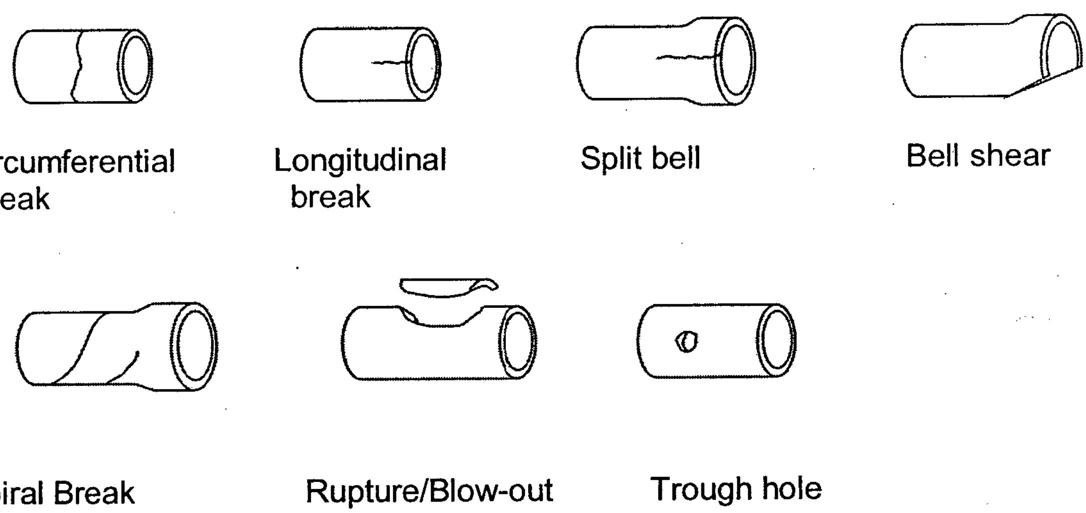


Figure 2-1: Types of Breaks of Water Mains (National guide 2003)

The potential consequences of failure in a given pipeline segment is the most important factor in determining the level and type of effort that should be invested in collecting the various types of data about the water mains. These consequences have been emphasized in a study carried out by Makar and Kleiner in 2000, in which they divided the costs of the consequences of failure into three categories. These categories are as follows:

- Direct costs (i.e. the cost of breakage repair, lost water cost, direct damage to property cost, and liabilities cost);

- Indirect costs (i.e. the accelerated deterioration of trenches, roads, sewers, underground cables, etc.);
- Social costs (i.e. the costs due to disruption of service, traffic, and business).

Because of the importance of these consequences, researchers are highly motivated to look for a comprehensive solution, taking into account current and future investment planning to enable municipal engineers and managers to take the most suitable and near optimum decision.

2.3 Condition Assessment of Water Mains

2.3.1 Introduction

Management of water mains is a complex process requiring knowledge of the physical condition of pipe being considered, in addition to the social and economic factors that affect the decision-making process. Currently two approaches are used: statistical approaches based on the historical numbers of pipe breaks per kilometer and inspection methods such as water auditing (Makar and Kleiner 2000). These approaches have been useful for managing water main failure. However, new technologies and knowledge about water pipe systems have made it possible to develop more efficient and accurate approaches for maintaining pipeline integrity (Makar and Rajani 2000).

Owing to the fact that metal pipes represent about 70% of the totality of water mains in North America, corrosion is the main cause of deterioration. Study carried out by Staples in 1996 revealed that the most promising non-destructive technologies for the sizing of corrosion pits are ultrasound and the remote field effect. It should be noted that Non-Destructive Evaluation (NDE) tools based on remote field effects is not affected by tuberculation. On the other hand, tuberculation may hamper or prevent water pipe inspections using ultrasonic methods.

Various efforts have been made to provide the decision makers with the most suitable inspection method. Makar and Chagnon (1999); Makar and Rajani (2000); Eiswirth *et al.* (2000); Burn *et al.* (2001) studied several inspection methods to gather information about pipe damage. They have divided these methods into two main groups. The first group uses direct inspection and monitoring techniques (**N**on **D**estructive **E**valuation). The second group uses the collection of data that can be used as indirect indicators of pipe problems, such as water audits, soil corrosivity measurements, half-cell potentials and pipe breakages. The latter indicator is the one that has been most commonly used in the past as a means of deciding when pipes should be replaced. Non-destructive evaluation (NDE) has certain advantages in detecting problems in pipes in comparison to data gathering and statistical methods. In the case of the latter, it is assumed that each pipe in a length that is being analyzed has the same condition. NDE can detect problems in individual pipes or at a particular point along an individual pipe, providing better information about pipe condition.

2.3.2 Direct Methods for Condition Assessment of Water Mains (NDE)

2.3.2.1 Acoustic-Based Leak Finder

These are portable microprocessor-based devices that pinpoint leaks automatically based on a cross-correlation method. In this method, acoustic leak signals are measured with vibration sensors or hydrophones at two pipe contact points (usually fire hydrants or valves) that bracket the location of a suspected leak. The leak signals are transmitted from the sensors to the correlator wirelessly. In most cases, the leak is located asymmetrically between measurement points. Consequently, there is a time lag between the measured leak signals. The time lag is found from the cross-correlation function of the leak signals. In the presence of a leak, the cross correlation function has a distinct peak at the time shift between leak signals. The location of the leak is calculated based on an algebraic relationship between the time lag, the sensor-to-sensor distance and the propagation velocity of sound waves in the pipe (Makar and Chagnon 1999, Hunaidi 2000, and Hunaidi *et al.* 2004).

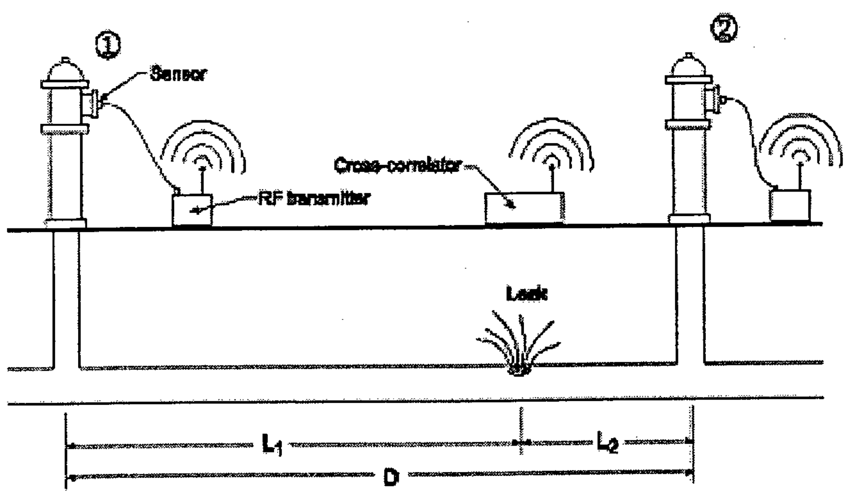


Figure 2-2: Acoustic Leak Finder (Hunaidi et al. 2004)

The distance from Fire hydrant (1) to the place of leak (L_1) can be calculated as follows:

$T_1 = L_1 / V$

$T_2 = L_2 / V$

$\Delta T = T_2 - T_1 = (L_2 - L_1) / V$

$L_2 = D - L_1$

$\Delta T = (D - 2L_1) / V$

$L_1 = (D - V \Delta T) / 2$

Where:

T_1: Arrival time of signal (1) to leak location (Sec)

T_2: Arrival time of signal (2) to leak location (Sec)

V: Sound propagation velocity in pipe (m/s)

ΔT: Time lag between signals 1 and 2(sec)

Limitation of the acoustical methods on Plastic Pipes

Acoustic leak-detection equipment has been developed mainly for metal pipes. Most professional users consider acoustic methods effective for finding leaks in metal pipes but problematic when used for plastic pipes. Leak signals in plastic and metal pipes have substantially different acoustical characteristics. Plastic pipes are "quieter" and do not transmit sound as efficiently as metal pipes. In addition, leak sounds in plastic pipes are dominated by low-frequency components (Hunaidi and Wing, 1999).

2.3.2.2 Thermography (Infrared) inspection technique

An infrared image is the result of the acquisition from the thermal radiation of the scene. The radiation produces a two-dimensional map representing the temperature, emissivity, and reflexivity variation of the scene (Neves et al 2003). The principle behind the use of thermography for leak detection is that water leaking from an underground pipe changes the thermal characteristics of the adjacent soil. The resulting thermal anomalies that occur above pipes are detected with handheld, vehicle-mounted or airplane-mounted infrared cameras. Furthermore, infrared thermography comparing to other non-destructive techniques is harmless since it does not emit any radiation. It only records the infrared radiation emitted from the object that is under investigation. In addition, infrared thermography is an area-investigating technique whereas most of the other non-destructive methods are either point-testing or line-testing methods; additionally, infrared thermography testing may be carried out in both day (i.e. overcast condition, and ambient/pavement temperatures are lower than pipe temperature) and night. The main limitation of the infrared thermography technique is the inability of the technique to determine the exact dimensions (depth and thickness) of the localized defects. Another limitation of the thermography testing is that it can create false signals in the thermograms especially when there are foreign bodies on the surface (chewing gum, spots of color or oil, patching areas, shadows) or particular constructions in the paving (heat sealing compound, road joint). In order to avoid this problem, a comparison of the thermal images with visual images of the investigated area should be carried out. In addition to that, the infrared thermography technique cannot be used in very cold weather due to low solar heating (solar loading), which creates a low temperature difference and therefore the typical temperature signature of the subsurface defects cannot be created. In the inspection of infrastructure facilities field, Weil (1998) utilized infrared technology to inspect sewer pipes. In doing so, an infrared thermography scanning system was used to measure the surface temperature. The resulting data was displayed as computer images with areas that have different temperatures. These areas are distinguished either by different gray levels in a black-and-white image or by various colors in a colored image. The varying energy areas, represented by different gray levels or colors, showed various characteristics such as the presence of voids in the supporting soil or a leak in a utility pipe. The system consists of four modules: 1) an infrared scanner, 2) a microprocessor, 3) a data analysis software package and 4) image recording and retrieving devices. The infrared scanner, which is similar in appearance to a video camera, can be utilized to acquire data (i.e. images) about pipes that need to be inspected. The microprocessor processes the images so that different energy areas are represented with different colors. The data analysis software grabs frames from the videotaped infrared images and analyzes them to extract information about the different energy areas. The image recording and retrieving device stores images for later use. It should be noted that the system does not require digging or intervention in sewer pipes. In 1999 Maldague described the employment of infrared thermography as a cost-effective qualitative alternative to commonly used non-destructive techniques such as X-rays and ultrasound to assess the wall thickness of the damaged pipe.

More importantly, some of these methods allowed water utilities to prevent pipe breaks from occurring, rather than reacting to them (Makar and Changnon 1999, Rajani *et al.* 2000, Eiswirth *et al.* 2001, Burn *et al.* 2001, De Silva *et al.* 2002, and National Guide 2003).

2.3.2.3 General Limitations of (NDE)

Up until now, the costs of applying (NDE) were high. Consequently, its use is limited to certain applications and is economically feasible only when used for large portions of the distribution system. Furthermore, the lack of complete integration of results into a framework leads to decision makers being provided with incomplete information about their water mains being tested. However, until now, different inspection tools with suitable sensor arrangements were required for the different measurement tasks. This necessity results in high mobilization costs and the loss of pipeline throughput. A further problem, quite often, is that the data recorded with different inspection tools needed to be correlated. If this is not done, the defect indications present in the data sets of different inspection runs at the same locations might be overlooked or not considered correctly (Bosch *et al.* in 2004).

2.3.3 Indirect Methods for Condition Assessment of Water Mains

A general diagnosis of the actual structural state of municipal water infrastructure systems is needed. To make a diagnosis, one must collect and analyze data on the characteristics of water pipes and on their breakage histories (Makar and

Chagnon 1999, and Rajani and Makar 2000). Unfortunately, many municipalities have been rigorously recording breakage histories only for a decade, while their pipes have been in the ground for much longer (Pelletier *et al.* 2003). Rajani and Makar in 2000 noted that the most important information that should be collected for the condition assessment of water mains includes the following:

- Pipe information (i.e. pipe diameter, wall thickness, date of installation, depth of burial, and manufacturing spun/ cast)
- Soil condition, (i.e. soil type, soil pH, soil density, soil resistivity, and aeration quality).
- Installation information (laying condition, load factor)
- Operational conditions (water pressure, surge pressures, summer and winter air and water temperatures, wheel loads, vehicle impact factor, frost load factor)

In 1999 Makar and Chagnon described a method called Pipe Sampling that involves removing sections of pipe from distribution and transmission mains when the pipes are exposed both during the repair of breaks and on other occasions. The main goal of pipe sampling is to determine the condition of the local pipeline by examining the pipe material for deterioration. Pipe Sampling can also provide an opportunity to examine the success of rehabilitation methods such as lining or Cathodic protection if the condition of a main was known before its rehabilitation. Periodic sampling may be helpful in tracking the long-term deterioration of water mains. Ideally, a sample should be taken from every broken main even if a full-scale failure analysis is not being contemplated.

However, the cost of taking and analyzing the samples may preclude this frequency. Therefore, water utilities should establish a percentage of the total annual pipe failures wherever samples are to be collected. The location and timing of the samples collected each year should be based either on a set number of pipe breaks or on a set of specific locations within the water system (National guide 2003). Furthermore, tests on soil samples collected in the vicinity of the exhumed pipe samples provide additional information to predict corrosion pit growth. It should be noted that indirect approaches have been used to obtain corrosion pit characteristics by using empirical methods for pipes of the same age that were buried in the same soil type.

2.3.4 Condition Rating Models for Water Mains

Many researchers have studied factors that contribute to the deterioration of water mains. Their main goal was to develop or to improve predictive planning models (Barcos *et al.*1955, Newport 1981, Rajani *et al.* 2000, and Rajani and Kleiner 2001). Owing to the fact that there are so many factors affecting pipe failures and influencing maintenance decisions, it is a very complex process to develop such models to assess all the factors. The factors affecting pipe deterioration can be either time-dependent or static. Those factors that will not change over time are static factors, such as pipe diameter or pipe material. On the other hand, pipe age, water pressure and temperature, soil corrosivity, soil temperature, the water content of soil and previous pipe breaks are examples of random and time-dependent factors (Shamir and Howard 1979; Stone *et al.* 2002).

Recently, Al-Aghbar and Moselhi (2005) identified the main causes of water main deterioration. These causes can be clustered into environmental factors; inadequate preventive maintenance and asset management programs; inadequate funds and changed municipality priorities; and finally lack of information and staff. Recent reports have demonstrated that the water main breakage rate is increasing in North America. Najjaran *et al.* (2004) reported that almost 700 water main breaks are reported in North America every day, accounting for maintenance costs of about $1billion/year. To deal with the above-mentioned factors, several models have been developed for the condition rating of water mains. These models help decision makers establish effective management strategies. The following section describes some recent models and their limitations.

Currently Used Condition Rating Models

The office of water service in the UK (OFWAT 2002) has been using a condition-grading system since 1998. The criteria are a mix of life expectancy and breakage rate (i.e. number of breaks / km / year). This grading is widely used in several municipalities in the UK; the grading is summarized in Table 2-1. As shown in Table 2-1, the grades are given with both qualitative and quantitative definitions. This grading system focuses only on burst frequency and qualitative remaining useful life. Dillon and Harfan (2003) used their Asset Management System (AMS) to assess the condition of individual pipe segments and to estimate the remaining service life of water mains in the City of Moncton, Canada. A full condition assessment using their systematic approach incorporates indices such as physical (derived from pipe repairs, material, thickness and environment), functional (derived from capacity and water quality), associated infrastructure (fire hydrants, valves and private junctions), and socioeconomics (derived from claims, population, time, and traffic). In this study, they have focused on only the development of the physical integrity index based on sub-indices for the break history, the pipe wall thickness, the pipe material and age. The sub-index of pipe thickness was developed from pipe sampling programs.

Table 2-1: Condition Grades of Water Mains (OFWAT 2002)

Condition Grade	**General Meaning**
1	No failures, with steel, ductile iron or non-ferrous mains or communication pipes designed to current standards.
2	As 1, but not designed to current standards in relation to pressure ratings, manufacturers' specification of corrosion protection. Deterioration causing minimal influence on levels of service and less than 1 burst / km / annum.
3	Deterioration beginning to be reflected in deteriorating levels of service and/or increased operating costs. Less than 3 bursts / km / annum. Asset replacement/ renovation required within 10 years.
4	Asset nearing end of useful life, further deterioration likely, affecting levels of service with significant internal or external corrosion. Bursts from 3-5 / km / annum. Asset replacement/renovation required within medium term.
5	Asset substantially derelict with no residual life expectancy requiring urgent replacement/renovation. Bursts greater than 5 / km / annum

Table 2-2: Break Index Classification (Dillon and Harfan 2003)

Condition Index Range	Condition Assessment	Improvement	Level of Service (Breaks / 100km /year)
0.75 to 1.0	A - Excellent	no action required	<5
0.50 to 0.75	B- Acceptable	Possible action in the long term	Between 5 and 15
0.250 to 0.50	C- Poor	An action is required in the short term	Between 15 and 50
0 to 0.25	D- Critical	An immediate action is required	>50

As shown in Table 2-2, the index of conditions based on pipe break history is given, and four categories are defined according to the level of service due to the number of breaks per 100 km per year. A pipe is assigned to the worst category if it has had more than 50 breaks per 100 km per year (0.5 breaks/ km/ year). This sub-index will then be tied into the other two indices of pipe-wall thickness and pipe material/age to obtain a final rating of a pipe.

Yan *et al.* (2003) have proposed a methodology that assists engineers in prioritizing pipe inspection and pipe rehabilitation in water systems. It uses Fuzzy Composite Programming (FCP) to aggregate the individual pipe condition indicators into a final overall indicator. The method of FCP is based on multi-criteria decision-making (MCDM) techniques with fuzzy set theory. The FCP hierarchical structure is deployed to combine first-level fuzzy indicators that lead pipes to deteriorate into second-level fuzzy indicators. The first-level fuzzy indicators include pipe age, pipe diameter, pipe material, road loading, soil condition, and surroundings (environmental conditions). The second-level fuzzy indicators include pipe physical factors and environmental factors. By using an FCP hierarchical aggregation process, the final level fuzzy indicator, which is the pipe condition indicator, is gauged. The final level indicator is used as a criterion to rank the pipe's condition. A fuzzy ranking method is applied to rank the fuzzy number and convert fuzzy results into crisp numbers. The ranking values range from "0" to"1". The main limitation of the developed FCP model is that it covers only physical and environmental factors mentioned above. In addition, this model considers only one type of soil.

Geem (2003) has developed a decision-support system (DSS) for pipe condition assessment using a back-propagation neural network (BPNN) technique, but the data used in developing the model was arbitrarily generated. The developed BPNN model works based on seven input factors including pipe material, bedding condition, corrosion, temperature, trench width, pipe diameter, and pipe age. The output of the model is the condition rating, which is scaled from "0" to "1". A "0" value indicates that the pipe is in perfect condition, and a value of "1", indicates that the pipe is in poor condition.

Al-Barqaui and Zayed (2006) have developed a decision-support system (DSS) for pipe condition assessment using a back-propagation neural network (BPNN) technique. The data used in developing the model was collected from three municipalities in Canada. The developed BPNN model works based on eight input factors including pipe material, age, size (i.e. diameter), breakage rate, C-factor, depth of cover, type of surface and type of soil. The output of the model is the condition rating, which is scaled from "<3" to "9-10". Values of "<3" indicate that the pipe is in critical condition, and "9-10" values indicate that the pipe is in excellent condition.

As can be seen from the models described above, no model exists that can explicitly and quantitatively consider all the factors that affect the deterioration of water mains; in addition, no unified standards have yet been developed in North America.

2.4 Heat Balance at Pavement Surface

2.4.1 Factors affecting Thermal Contrast at Pavement Surface

It should be noted that, although the heat and moisture transfer in soil is multi-dimensional, the following one-dimensional state equations were reviewed to appreciate heat and moisture transfer in soil

At the top of the pavement surface, four modes of heat transfer are considered: conduction into the pavement layer, convection, solar absorption, and grey-body irradiation to the surrounding.

$$Q_{cond} = K_{cond} * (T_0 - T_1) / L \ (W/m^2) \tag{2-1}$$

Where K_{cond} is the thermal conductivity of the pavement in (w/m ^{0}c), T_0 and T_1 are the surface temperature and internal temperature of the pavement at first node respectively and L is the length of the flow path, assuming steady-state heat flow in one direction (ASHRAE 1977; Hutcheon and Handegord 1983; Bentz 2000) . For convection, the heat flow is given by:

$$\mathbf{Q_{conv} = h_{conv} * (T_0 - T_{ambiant})\ (W/m^2)} \qquad \textbf{(2-2)}$$

Where $T_{ambient}$ is the ambient temperature and h_{conv} is the convection coefficient in (w/m ^{0}c)

$$\mathbf{h_{conv} = 5.6 + 4.0\ V_{wind}} \qquad \textbf{for } \mathbf{V_{wind} \leq 5\ m/s} \qquad \textbf{(2-3)}$$

$$\mathbf{h_{conv} = 7.2 * (V_{wind})^{0.78}} \qquad \textbf{for } \mathbf{V_{wind} > 5\ m/s} \qquad \textbf{(2-4)}$$

Where V_{wind} wind speed in m/s (Schlangen 2000).

For radiative heat transfer at the top pavement surface, two contributions are considered the first is radiation absorbed from the incoming sunlight. For incoming heat flow due to this source is given by

$$\mathbf{Q_{sun} = \gamma_{abs} \times Q_{inc}\quad (W/m^2)} \qquad \textbf{(2-5)}$$

Where Q_{inc} is the incident solar radiation (W/m^2) and γ_{abs} is the solar absorptivity of the pavement (McCullough et al. 1999). The second contribution considered is the emission of radiation from the "warm" pavement to the sky

$$\mathbf{Q_{sky} = \sigma\, \epsilon \times (T^4_{0k} - T^4_{sky})\quad (W/m^2)} \qquad \textbf{(2-6)}$$

Where σ is the Stefan-Boltzmann constant (5.669×10^{-8} W/m^2 ^{o}C^4), ϵ is the emissivity of the pavement (Hutcheon and Handegord 1983; Bentz 2000). In this research values of ϵ = 0.90 for concrete pavement and 0.94 for asphalt pavement (Moher 2006) are used, respectively. T_{0k} is the pavement surface temperature (in K), and T_{sky} is the calculated sky temperature in K.

The sky temperature is estimated based on an algorithm presented by Walton in 1985, using the following series of equations:

$$\mathbf{T_{sky} = \epsilon_s^{0.25} \times T_{ambient}} \quad \textbf{(2-7)}$$

ϵ_s sky emissivity is given by

$$\mathbf{\epsilon_s = 0.787 + 0.764 \times \log_e (T_{dew}/273) \times F_{cloud}} \quad \textbf{(2-8)}$$

Where:

T_{dew} is the dew point temperature in K and with the cloud cover factor, F_{cloud}, as:

$$\mathbf{F_{cloud} = 1.0+0.024N-0.0035N2+0.00028N3} \quad \textbf{(2-9)}$$

N is the "tenth cloud cover", taking values between 0.0 and 1.0

2.4.2 Heat and Moisture Transfer in Soil

Migration of heat and moisture in soil is a coupled energy and mass transport process, which is affected by the field distribution of temperature, pressure, and velocity (Liu *et al.* 2005). Soil heat transfer in the unsaturated zone of the soil is the sum of fluxes due to heat conduction and convection. The soil heat flow can be expressed as

$$C_s(\theta) \frac{\partial T}{\partial t} = \frac{\partial}{\partial z} (\lambda (\theta) \frac{\partial T}{\partial z}) - C_w \, q \frac{\partial T}{\partial z} \quad \textbf{(2-10)}$$

Where:

T: is the soil temperature in ^{0}C;

λ (θ): is the thermal conductivity of soil in W cm^{-1} K^{-1};

C_s and C_w: are the volumetric specific heats in J cm^{-3} K^{-1} for soil porous media and water, respectively;

q: is the volumetric flux of water (or Darcy velocity) in cm day^{-1} (Sung et al. 2002).

The volumetric specific heat $C_s(\theta)$ of the soil can be calculated by the addition of the heat capacities of the various phases (De Vries and Afgan 1975), as follows:

$$\mathbf{C_s = C_w\, \theta_w + C_a\, \theta_a + C_o\, \theta_o + C_m\, \theta_m} \qquad \textbf{(2-11)}$$

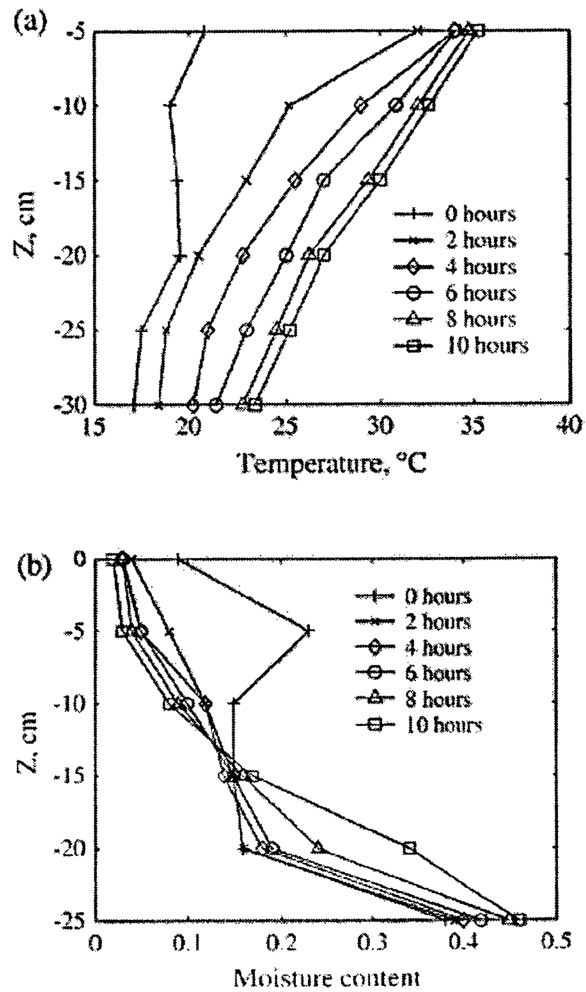
Where: C_i and θ_i are the specific heat and the volumetric content of each i th component, respectively. The subscripts w, a, o, m indicate water, air, organic matter and mineral of the soil, respectively.

Horton and Chung (1991) simplified equation (2-11) as follows:

$$\mathbf{C_s = (1 - \theta_s) \times 1.92\times10^6 + 4.18\times10^6\, \theta} \qquad \textbf{(2-12)}$$

Where: θ_s is the soil water content at saturation; and θ is the soil water content; and C_s is the volumetric specific heat in J m^{-3} $^oC^{-1}$

Chen *et al.* (2006) studied the movement of heat, moisture and salt transfer in sand and loam soils and the factors that affect these movements. The study revealed that there are different moisture transfer zones as shown in Figure 2-3(b). The heat flux and temperature has great influence on the moisture transfer; a high heat flux will enhance the evaporation; however, if the temperature is too high and the surface soil is dried in a short time, the capillary transfer is broken down and evaporation will occur; it will prevent the inner moisture loss and decrease the moisture transfer rate. In addition, the influence of air convection is also very important; the evaporation rate under air convection and radiation should be greater than that of pure high radiation despite the temperature of the latter being higher. With the moisture transfer, the salt will be taken from the ground to the surface and it accumulates. With the accumulation, there will be a gradient of salt content. The salt will also diffuse under this gradient force.



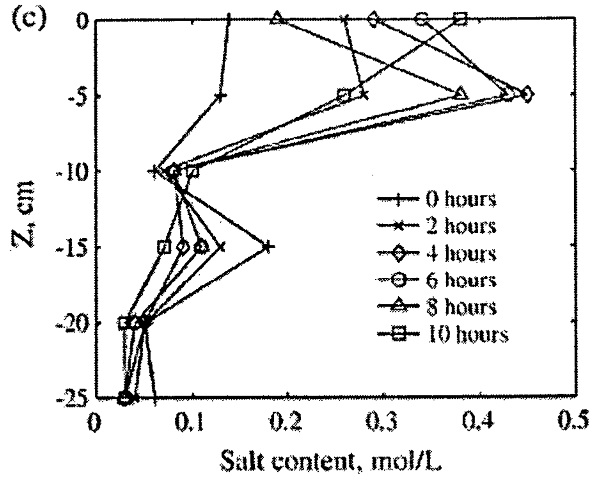


Figure 2-3: Transient Distribution of: (a) Temperature, (b) Moisture content, (c) Salt content (Chen *et al.* 2006)

2.4.3 Thermography Application

The electromagnetic spectrum is divided arbitrarily into a number of wavelength regions, called "bands" as depicted in Figure 2-4. Thermography makes use of the infrared spectral band from 2µm (i.e. at visual perception limit) to 14µm (Garcia *et al.* 2002).

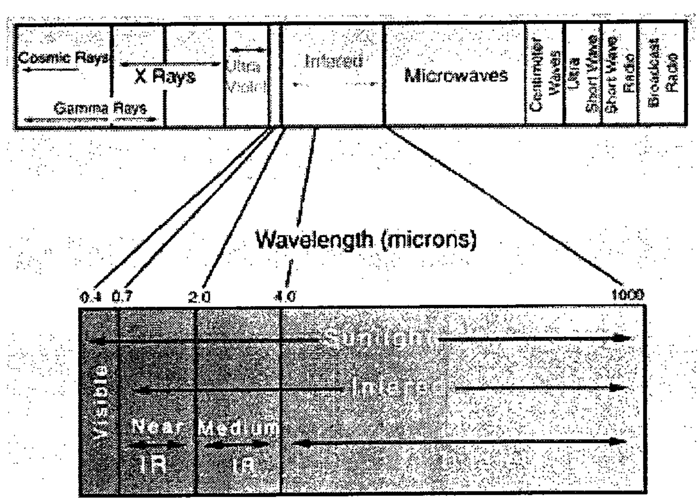


Figure 2-4: The Electromagnetic Spectrum (Watershed 2006)

2.4.4 Blackbody Radiation

A black body is an object that absorbs all electromagnetic radiation that falls onto it. No radiation passes through it and none is reflected (Hutcheon and Handegord 1983). If the body is a perfect radiator (i.e. blackbody), it will radiate in accord with Plank's equation as follows:

$$\mathbf{W_{b\lambda} = 3.74 \times \lambda^{-5} \times 10^{8} / (e^{14400/\lambda T} - 1) \ (W/(m^2 . \mu m))} \qquad \mathbf{(2\text{-}13)}$$

Where:

$W_{b\lambda}$: blackbody emissive power for the unit wavelength interval of 1 μm at wavelength λ in micrometers for the temperature T in Kelvin.

By differentiating Planck's equation with respect to λ, and finding the maximum, we have Wien's equation as follows

$$\mathbf{\lambda_{max} = 2898/T \ (\mu m)} \qquad \mathbf{(2\text{-}14)}$$

Wien's equation expresses mathematically the common observation that colors vary from red to yellow as the temperature of the thermal radiator increases. The wavelength of the color is the same as the wavelength calculated for $\boldsymbol{\lambda_{max}}$.

By integrating Planck's equation from $\lambda = 0$ to $\lambda = \infty$ (i.e. the area under any of the curves of Figure 2-5, we obtain the total radiant emmittance (W_b) as follows:

$$\mathbf{W_b = \sigma T^4 \ (W/m^2)} \qquad \mathbf{(2\text{-}15)}$$

Where: σ = the Stefan-Boltzmann constant = 5.7×10^{-8}

Equation (2-15) represents Stefan-Boltzmann's equation, which states that the total emissive power of a black body is proportional to the fourth power of its absolute temperature. However, real objects almost never comply with this equation, because they reflect some radiation, consequently most real bodies radiate at a rate less than that of a blackbody at a given temperature (Hutcheon and Handegord 1983). The emissive power of a non-black surface given by

$$W = \epsilon W_b = \epsilon \sigma T^4 (W/m^2) \qquad (2\text{-}16)$$

Where: ϵ is the object emissivity that is less than unity (e.g. from 0.1 to 0.95)

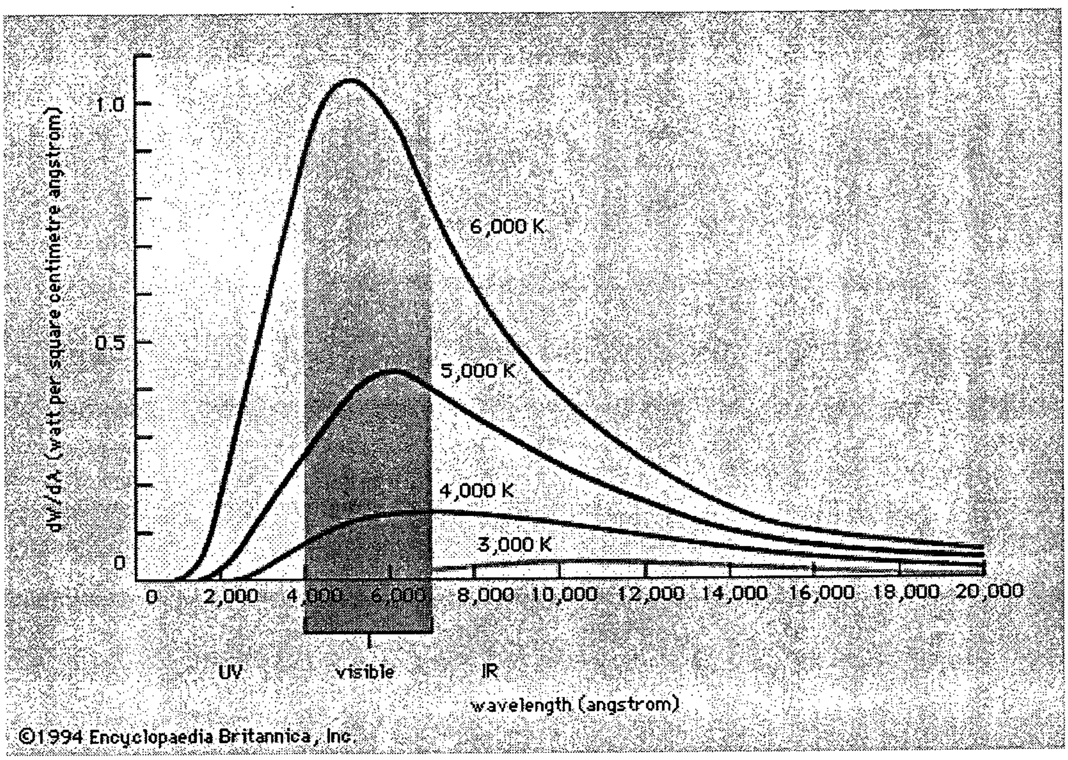


Figure 2-5: Radiation from a Black Body at Various Temperatures

(Source: Encyclopedia Britannica 1994)

2.4.5 Thermographic Measurement Technique

The thermography camera (IR camera) measures and images the emitted infrared radiation from an object. The fact that radiation is a function of object surface temperature makes it possible for the camera to calculate and display this temperature (FLIR Systems 1999). However, the radiation measured by the camera not only depends on the temperature of the object but is also a function of the emissivity. Radiation also originates from the surroundings and is reflected in the object. The radiation from the object and the reflected radiation will also be influenced by the absorption of the atmosphere.

To measure the temperature accurately, it is therefore necessary to compensate for the effects of a number of different radiations. Therefore, the following object parameters must be supplied for the camera:

1) The emissivity of the object; 2) the ambient temperature; 3) the distance between the object and the camera; and 4) the relative humidity

2.5 Artificial Neural Networks (ANNs)

Work on Neural Networks has been motivated right from its inception by the recognition that the way the human brain computes is entirely different from the way the conventional digital computer computes. The brain is a highly complex, nonlinear, and parallel computer (information-processing system). It has the capability of organizing its structural constituents, known as neurons, to perform certain computations (e.g. pattern recognition) (Haykin 1999). Furthermore, it has the ability to learn from input data with or without a teacher. It is apparent that a neural network derives its computing power through, first, its parallelly distributed structure and, second, its ability to learn and therefore to generalize. Generalization refers to the neural network's ability to produce reasonable output- inputs not encountered during training (learning). These two powerful attributes make it possible for neural networks to solve complex (large-scale) problems that are currently intractable (Zurada 1992; Haykin 1999; Peter 2004).

2.5.1 Learning paradigm

Learning is a process by which the free parameters of a neural network adapt through a process of stimulation by the environment in which the network is embedded. The type of learning is determined by the manner in which the parameter changes take place. This definition of the learning process implies the following sequence of events: 1.The neural network is stimulated by an environment; 2. The neural network undergoes changes in its free parameters because of this stimulation; 3. The neural network responds in a new way to the environment because of the changes that have occurred in its internal structure.

2.5.2 Supervised learning

This is also referred to as "learning with a teacher." The network is modeled to solve some difficult and diverse problems through training in a supervised manner. A highly popular algorithm known as the error back-propagation algorithm is used. As depicted in Figure 2-6, the teacher is considered as having knowledge of the environment, that knowledge being represented by a set of input-output examples. Suppose that the teacher and the neural network are both exposed to a training vector (i.e. example) drawn from the environment, where the teacher is able to provide the neural network with a desired response for that training vector. The optimum action is to be performed by the neural network. The network parameters are adjusted under the combined influence of the training vector and the error signal, which is defined as the difference between the desired response and the actual response of the network. This adjustment is carried out iteratively in a systematic fashion with the aim of eventually making the neural network emulate the teacher; the emulation is presumed to be optimum in some statistical sense (Zurada 1992; Haykin 1999; Peter 2004).

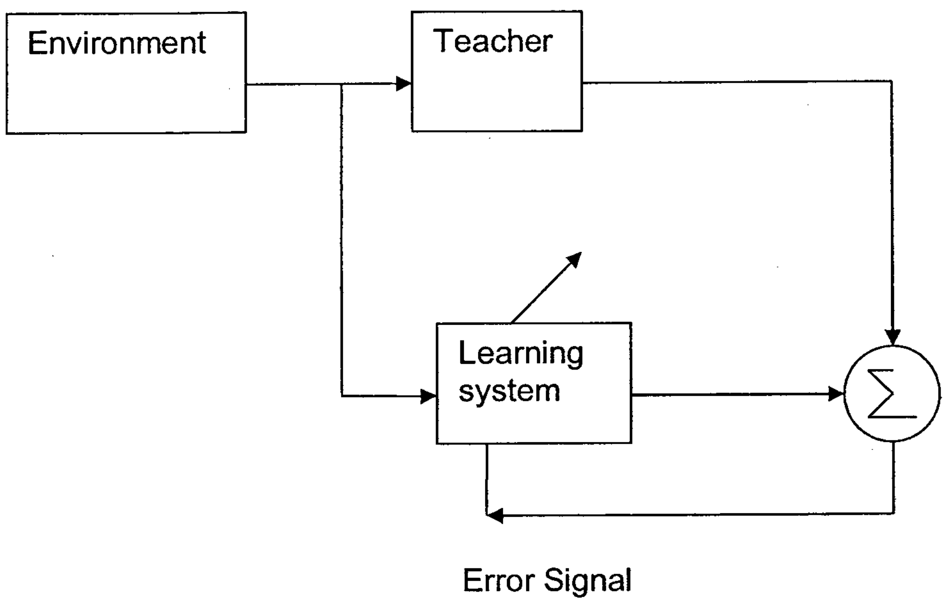


Figure2-6: Block diagram of a learning with a teacher (supervised)

Error Back- Propagation (Haykin 1999)

2.5.3 Back Propagation Neural Network

Back propagation Neural Network was created by generalizing the Widrow-Hoff learning rule to multiple layer networks and non-linear differentiable transfer function. Input vectors and corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way. Networks with biases, a sigmoid layer and a linear output layer are capable of approximating any function with a finite number of discontinuities. The back propagation algorithm consists of two paths; forward path and backward path. Forward path involves creating a feed forward network, initializing weight, simulation and training the network. The network weights and biases are updated in the backward path. A network with five inputs is shown in Figure 2-7.

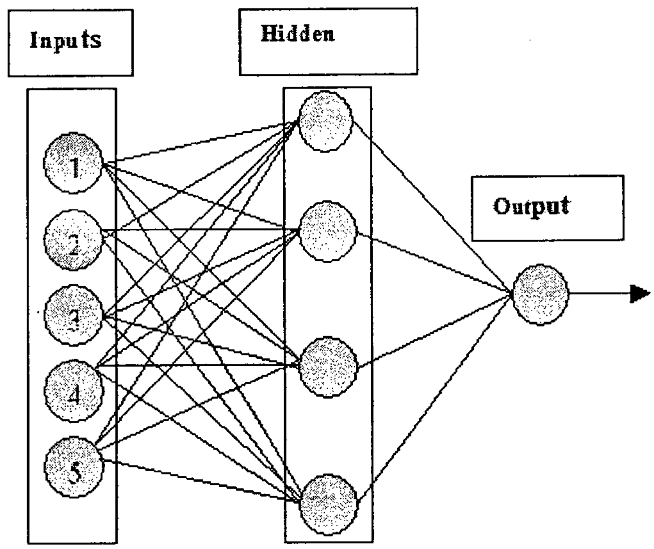
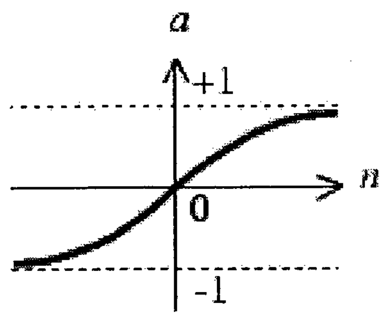


Figure 2-7: Typical Architecture of a Back Propagation Neural Network

Feed forward networks often have one or more hidden layers of sigmoid neurons followed by output layer of linear neurons. Multiple layers of neurons with non-linear transfer functions allow the network to learn non linear and linear relationships between input and output vectors. The linear output layer lets the network produce values outside the range -1 to +1 (Figure 2-8).



a=Sin (n)

Figure 2-8: Sigmoid Transfer Function

On the other hand, if we want to constrain the outputs of the network between 0 and 1, then the output layer should use a log-sigmoid transfer function. Before training a feed forward network, the weight and biases must be initialized. Once the network weights and biases have been initialized, the network is ready for training. Random numbers are used around zero to initialize weights and biases in the network. The training process requires a set of proper inputs and targets as outputs. During training, the weights and biases of the network are iteratively adjusted to minimize the network performance function. The default performance function for feed forward networks is mean square errors, i.e., the average squared errors between the network outputs and the target output.

2.5.3.1 Back Propagation Algorithm

1. Propagates inputs forward as follows:

- All outputs are computed using sigmoid thresholding of the inner product of the corresponding weight and input vectors.

- All outputs at stage n are connected to all the inputs at stage $n+1$

2. Propagates the errors backwards by apportioning them to each unit according to the amount of this error the unit is responsible for.

Backpropagation algorithm for the general case:

$\vec{x_j} =$ Input vector for unit j (x_{ji} = ith input to the jth unit)

$\vec{w_j} =$ Weight vector for unit j (w_{ji} = weight on x_{ji})

$z_j = \vec{w_j} \cdot \vec{x_j}$ The weighted sum of inputs for unit j

$o_j = \sigma(z_j)$ o_j = output of unit j

t_j = target for unit j

Downstream (j) = set of units whose immediate inputs include the output of j

Outputs = set of output units in the final layer.

the error denoted by E, to calculate $\frac{\partial E}{\partial wji}$ for each input weight w_{ji} for each output unit j. Note first that since z_j is a function of w_{ji} regardless of where in the network unit j is located,

$$\begin{aligned}\frac{\partial E}{\partial w_{ji}} &= \frac{\partial E}{\partial z_j} \cdot \frac{\partial z_j}{\partial w_{ji}} \\ &= \frac{\partial E}{\partial z_j} x_{ji}\end{aligned}$$

Furthermore, $\frac{\partial E}{\partial zj}$ is the same regardless of which input weight of unit *j* we are trying to update this quantity is denoted by δj.

Consider *j* ∈ outputs, thus

$$E = \frac{1}{2} \sum_{k \in Outputs} (t_k - \sigma(z_k))^2$$

Since the outputs of all units k≠ j are independent of w_{ji}, we can drop the summation and consider just the contribution to *E* by *j*.

$$\begin{aligned}\delta_j = \frac{\partial E}{\partial z_j} &= \frac{\partial}{\partial z_j} \frac{1}{2}(t_j - o_j))^2 \\ &= -(t_j - o_j)\frac{\partial o_j}{\partial z_j} \\ &= -(t_j - o_j)\frac{\partial}{\partial z_j}\sigma(z_j) \\ &= -(t_j - o_j)(1 - \sigma(z_j))\sigma(z_j) \\ &= -(t_j - o_j)(1 - o_j)o_j\end{aligned}$$

Thus

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_i j} = \eta \delta_j x_{ji}$$

For each output unit *k*,

$$\delta_k = o_k(1 - o_k)(t_k - o_k)$$

For each hidden unit *h*,

$$\delta_h = o_h(1 - o_h) \sum_{k \in Downstream(h)} w_{kh}\delta_k$$

Thus, the update of each network weight w_{ji} can be calculated as follows:

$$\begin{aligned} w_{ji} &\leftarrow w_{ji} + \Delta w_{ji} \\ \text{where} \quad \Delta w_{ji} &= \eta \delta_j x_j i \end{aligned}$$

A momentum term can be added to the weight update rule as follows:

$$\Delta w_{ji}(n) = \eta \delta_j x_{ji} + \alpha(n-1) w_{ji}$$

Where

$$0 \leq \alpha < 1$$

α is a constant called the *momentum* and *n* is the iteration number (Venkataraman 1999) .

2.5.4 General Regression Neural Network

GRNN Algorithm

The GRNN is a multilayer feedforward (i.e. signals propagate only in a forward direction) neural network that performs general regression analysis directly from sample data for the purpose of prediction. Unlike traditional regression, the GRNN does not require a specific functional form, requiring the dependent (target) and independent (input) variables to be assumed. Instead, it allows the appropriate form to be expressed as a probability density function of the observed data.

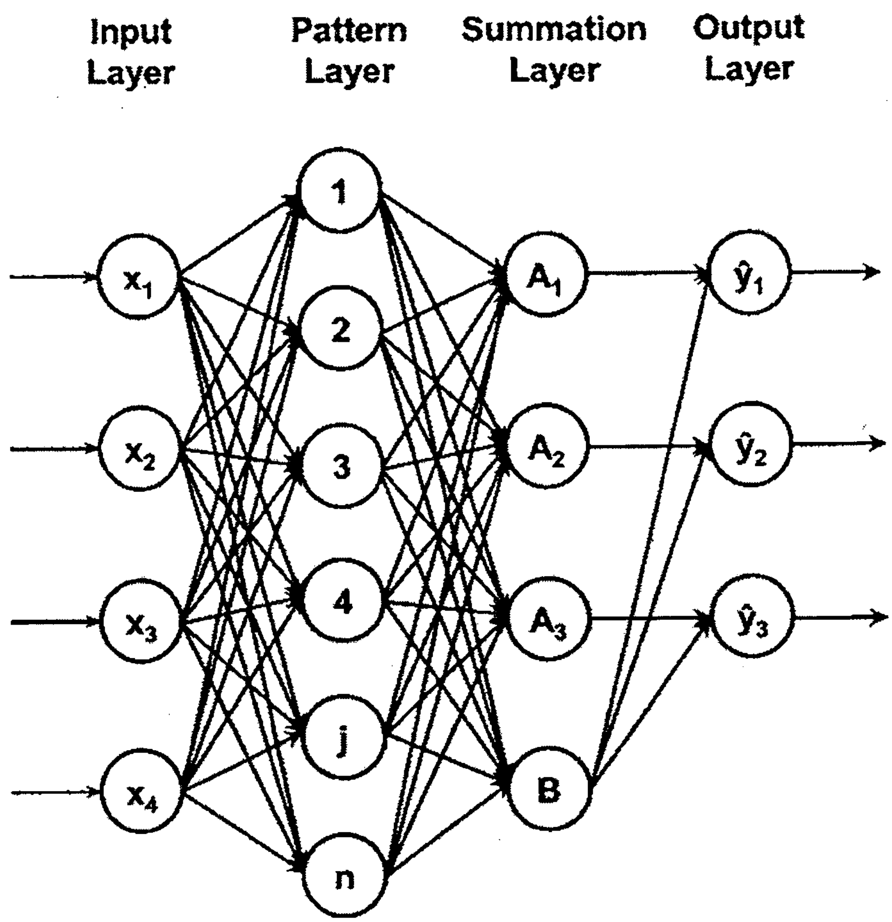


Figure 2-9: The GRNN Model Architecture

The governing equation of the GRNN is as follows:

$$\hat{y} = \frac{\sum_{j=1}^{n} y_j \exp\left(\frac{-\sum_{i=1}^{m} (x_i - x_{ij})^2}{2\sigma^2} \right)}{\sum_{j=1}^{n} \exp\left(\frac{-\sum_{i=1}^{m} (x_i - x_{ij})^2}{2\sigma^2} \right)} \qquad (2\text{-}18)$$

Where: m = number of input variables; n = number of training cases; x_i = value of the ith variable of the given testing case; x_{ij} = value of the ith variable of the jth training case; y_j = value of the target variable of the jth training case; σ = smoothing parameter that determines how closely the function implemented by the GRNN fits the training data; and $\hat{y}$ = estimated target value corresponding to the given testing case. Essentially, the GRNN computes the (Euclidean) distance separating the input values of a given testing case (x_i) from those of each training case (x_{ij}) and then finds the weighted mean of the target values of the training cases (y_j) closest to the testing case to predict the network output ($\hat{y}$). As can be seen from Equation 2-18, when the distance separating the testing case and a training case is very small, the corresponding target value (y_j) is weighted heavily in the estimate $y\hat{}$; and when the distance separating the testing case and a training case is very large, the corresponding target value (y_j), contributes very little to the weighted mean. It can also be seen that as σ gets very large, the estimate $\hat{y}$ becomes the mean of the observed values (y_j) ; and as σ becomes very small, the estimate $\hat{y}$ takes on the values of the (y_j) associated with the observation nearest to x_i (Specht 1991). Thus, when the data are known to be clean, σ may be very small so that the function implemented by the GRNN provides an accurate fit to the training data. In the case of noisy training data, the value of σ must be increased to eliminate the effects of any wild points on the estimated function and provide greater generalization between the data points.

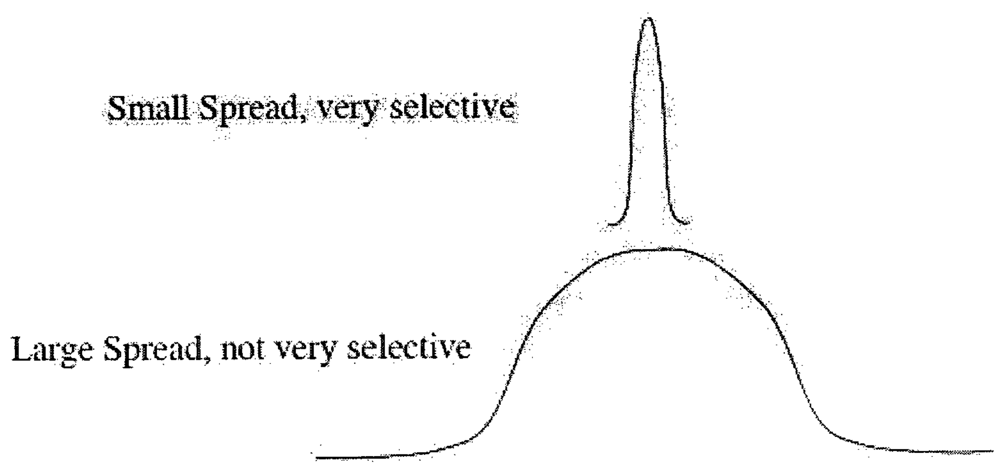


Figure 2-10: The sigma value (σ) of the function determines the spread of the RBF function

There are numerous advantages of using the GRNN, especially compared to the more widely used back-propagation neural network algorithm. The back-propagation neural network algorithm must be trained in an iterative manner and has a tendency to converge to local minima instead of finding the global minimum of the error surface (often arriving at a poor solution when a much better one exists). Whereas the GRNN learns in one pass through the training set (no iterative computations are required) and does not converge to local minima (Specht 1991). As the number of samples increases, the estimate $\hat{y}$ converges to the conditional mean regression surface, although very reasonable regression surfaces are formed based on only a small number of samples. This makes the GRNN particularly useful when the amount of training data are limited, and is an advantage over the back-propagation model, which tends to require more data to achieve comparable results. Another advantage noted by (Specht 1991) is that the estimate is bounded by the minimum and maximum of the observations; the GRNN cannot produce an estimate outside the range of observed samples *yj*. Finally, depending on the training set used, may be made either larger to smooth out noisy data or smaller to allow an accurate and close fit of relatively clean data.

The GRNN, though, is not without limitations. The main disadvantage of this neural network is the substantial amount of computation (and time) required of the trained system to evaluate a new point. In addition, although the GRNN will not give wild predictions, as the estimate is bounded by the range of observed values, the network is not capable of extrapolation, which means that the training data must encompass the full range of expected output values if accurate results are to be achieved. In addition, the GRNN tends to underestimate the output values when the testing data fall within the proximity of the peak of the output surface, and tends to overestimate the output values when the testing data fall near the trough of the output surface. Back propagation-based neural networks do not necessarily suffer from this drawback.

2.6 Protection of Metallic Water Mains (Cathodic Protection)

Cathodic protection is the electrical method of preventing a corrosion attack on metallic piping. It has been widely used by a number of water municipalities as a means to ensure long-term operational performance (Rajani *et al.* 2000; Kroon 2001; Lary 2003). It is also a viable measure to extend the residual life of water mains and thus defer capital investments in their rehabilitation and renewal. The effectiveness of cathodic protection varies with the unique set of conditions under which it is applied (Kliner and Rajani 2004). In the management of large infrastructures, the cost of corrosion prevention is relatively small when compared to the cost of total replacement or substantial rehabilitation (Paul and Connor 2003). In 1994, Kirmeyer *et al.* estimated that, in the United States, more than two-thirds of all existing water pipes were metallic (about 48% cast iron and 19% ductile iron), about 15% were asbestos-cement, and the remaining 18% were plastic, concrete and others. A survey encompassing (21) Canadian cities (about 11% of the population of Canada), conducted by Rajani and McDonald (1995), revealed a similar distribution of pipe material types. In most North American cities, metallic water mains deteriorate because of aggressive soil conditions, the use of dissimilar metals and because of stray electric currents due to electrical grounding or other sources of currents, etc. These conditions encourage external corrosion pits in ductile iron or the formation of graphitized zones in cast iron. Furthermore, under extreme conditions, corrosion can affect pipe integrity as early as 5 years after installation (Kleiner and Rajani 2004).

There are two methods of applying cathodic protection. One method of protection makes use of galvanic anodes that have a natural difference of potential with respect to the structure to be protected. As shown in (Figure 2-11), these anodes are made of a material, such as magnesium or zinc, which is anodic with respect to the protected structure.

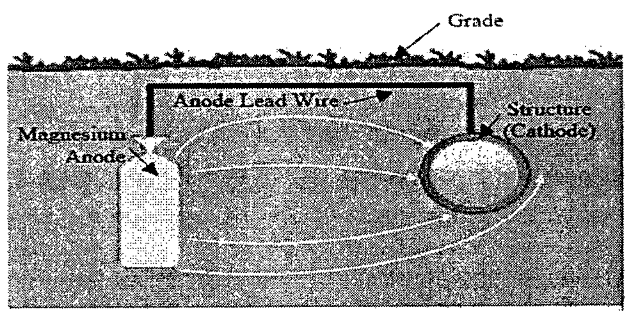


Figure 2-11: Galvanic Anode Cathodic Protection (Waters 2001)

The anode lead wire is connected directly to that structure or through a test station. The test station allows for system monitoring after installation. The limitations of utilizing the sacrificial CP system could be its limited current output, and it is not economically justified in high resistivity media (such as soil with resistivities above 5,000 ohm-cm), its installation may be expensive (particularly when installed under concrete), and moisture in the soil is very critical. An anode will operate in moist soil and may not operate in the same soil during dry seasons.

The other method uses anodes that are energized by an external DC power source (Figure 2-12). In this type of Cathodic protection system, anodes are installed in an electrolyte (soil or water) and connected to the positive terminal of the DC source; the structure, which is to be protected, is connected to the negative terminal of that source.

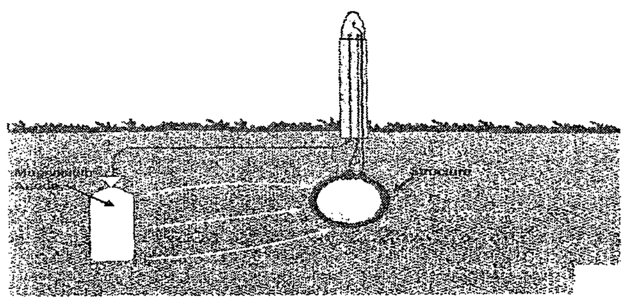


Figure 2-12: Impressed Current System

The limitations of the impressed current system could be it needs careful design to avoid Cathodic interference, is affected due to power failure and outside interference, requires inspection and maintenance, requires constant alternating current power, which may be costly over the life of the unit. In general, the application of Cathodic protection is an economical and effective means of controlling corrosion on water systems. The success of the Cathodic protection system is dependent on proper design and effective monitoring (Waters 2001, and Lary 2003).

2.7 Rehabilitation/ Replacement Methods

For any type of buried infrastructure, an understanding of the type and condition of the soil and of any possible infrastructure conflicts is critical (National Guide 2003). Depending on soil conditions, water table levels and cost factors, the options for rehabilitating, replacing, or repairing a water main section may be limited. As such, a geotechnical investigation is normally undertaken to confirm the soil conditions and any possible infrastructure conflicts before designing any options to rehabilitate or replace a section of water main.

2.7.1 Factors that Affect the Selection of Appropriate Rehabilitation / Replacement Technologies

Many factors affect the selection of the appropriate rehabilitation technology. These factors include but not limited to financial factors, social factors, the locality of the technology (e.g. its availability in Canada), and water main material. Finances always play an important role in water main rehabilitation or replacement. A structured approach should be suggested including a prioritization process to determine which section of water main should be maintained, rehabilitated or replaced first. An infrastructure rehabilitation / replacement plan should be prioritized based on the overall best value to the community. It should be noted that community issues come into play when determining which section of water main is to be rehabilitated or replaced. These issues include but not limited to population growth, environmental concerns, urban and rural development issues, health and safety, the impact on businesses, risk of failure, other infrastructure co-ordination issues (e.g. sewer and roads primarily) and the criticality of the water service (e.g. water supplied to a hospital). Furthermore, local availability is also critical in that some regions across Canada may have very little access to some of the new technologies. Finally, the selection of the water main material may have an impact on the rehabilitation or replacement technology (Moselhi and Shehab- Eldeen 2001; National Guide 2003; Najafi and Kim 2004; Al-Aghbar and Moselhi 2005; Shehata 2006).

2.7.3 Open Cut Technique

The installation of new water mains by continuous trenching is frequently referred to as the open cut method (Kramer *et al.* 1994). The installation of new replacement pipe should be undertaken only when the review of all alternate technologies has been completed and the open cut method is ranked as the best alternative.

2.7.4 Trenchless Technology (no or less dig)

Street works become an everyday occurrence and can take the form of highway works involving either carriageway reconstruction or resurfacing or utility works involving either the installation of new networks or the repair of existing services (Howell 2004). However, some level of delay and disruption is unavoidable during the construction phase. This delay and disruption of course incurs costs in terms of lost time and the use of extra resources. This cost is difficult to quantify and is not usually taken into consideration in the overall cost of the works. The Transport Research Laboratory (TRL) estimates that this indirect cost of trenching is about twice the installation cost of all utility installation works each year (Howell 2004). These above-mentioned factors have led researchers to develop the trenchless technology for rehabilitation / replacement of water mains and it improves quality, reduces cost and project duration. This technology is being widely used in water mains rehabilitation / replacement.

Trenchless Technology (TT) is the technology for placing new pipe, cable, or conduit in the ground between two defined points, without continuous open-cut excavation between them. Furthermore, this technology can also be utilized effectively for the rehabilitation of underground pipes and/or for innovation purposes (Kramer *et al.* 2002 and 2004). Previous studies have revealed that Trenchless Technology can significantly reduce the environmental impact of underground utility works. By minimizing surface disruption, traffic congestion is significantly reduced, thereby reducing the generation of air pollution and greenhouse gases. TT can also reduce the amount of waste generated by decreasing earth and pavement excavation and by utilizing existing piping materials. These studies also reveal that TT has advantages over the open cut (trench) method. It can substantially reduce disruption as it offers greater productivity due to faster installation times, reduced access requirements and smaller footprint size because less excavation is required. In addition, it improves also the hydraulic characteristics of the host pipe. Furthermore, it is more environmentally friendly since there are fewer requirements for landfill space and quarried backfill materials. Moreover, it can also prevent tree root damage, which is a major hazard when open trench methods are employed (Mckim 1997; Moselhi and Shehab-Eldeen 2001; Gumbel 2001; Kliner and Rajani 2002; Zhao

2003; Howell 2004; Heavens and Jason 2004; Najafi and Kim 2004; Moselhi and Al-Aghbar 2005; and Shehata 2006). McKim (1997) has proposed methodologies for estimating social costs and suggested that including social costs in the bidding process makes trenchless technology more cost effective. Najafi and Kim in 2004 studied a comparison of the life-cycle-costs between open-cut and trenchless pipeline construction. This study included a breakdown of the engineering and capital costs of the construction and the social costs for both methods. The analysis revealed that trenchless technology is more cost-effective than the traditional open-cut method. Appendix A- 5 illustrates the selection of appropriate technology for rehabilitation/ replacement of water mains; in addition, appendixes A-6, A-7 and A-8 show the several types of trenchless technologies, presenting their use, advantages and drawbacks.

Summary and Concluding Remarks

This chapter describes structure failure modes and current practices in condition assessment of water mains, along with various methods used for their rehabilitation, specifically focusing on trenchless technologies. The limitations of current practices are also discussed. As described the deterioration and rehabilitation methods of water mains varies due to their types, surrounding soil and operating conditions. In order to mitigate the risk of water main failure, municipal engineers need effective methods to provide reliable condition assessment of the pipes being considered, prioritize the rehabilitation actions, and recommend the most suitable method for maintenance and/or rehabilitation that saves time, cost and improves safety.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 General

The methodology adapted in the research involved a comprehensive literature review in the area of condition assessment of water mains, in addition to interviews with experts and the analysis of actual data collected from various municipalities in Canada and the US. Additionally, field study and onsite experiments were conducted in greater Montreal, Quebec. A pictorial representation of the adopted methodology is given in Figure 3-1.

3.2 Literature Review

A comprehensive literature review is carried out in the areas of condition assessment and rehabilitation of water mains including factors contributing to their deterioration, structural failure modes, in addition to evaluation and rehabilitation methods. Furthermore, thermography applications and factors that affect the thermal contrast at pavement surface due to water leaks were considered, including heat and moisture transfer in soil, and heat balance at pavement surface.

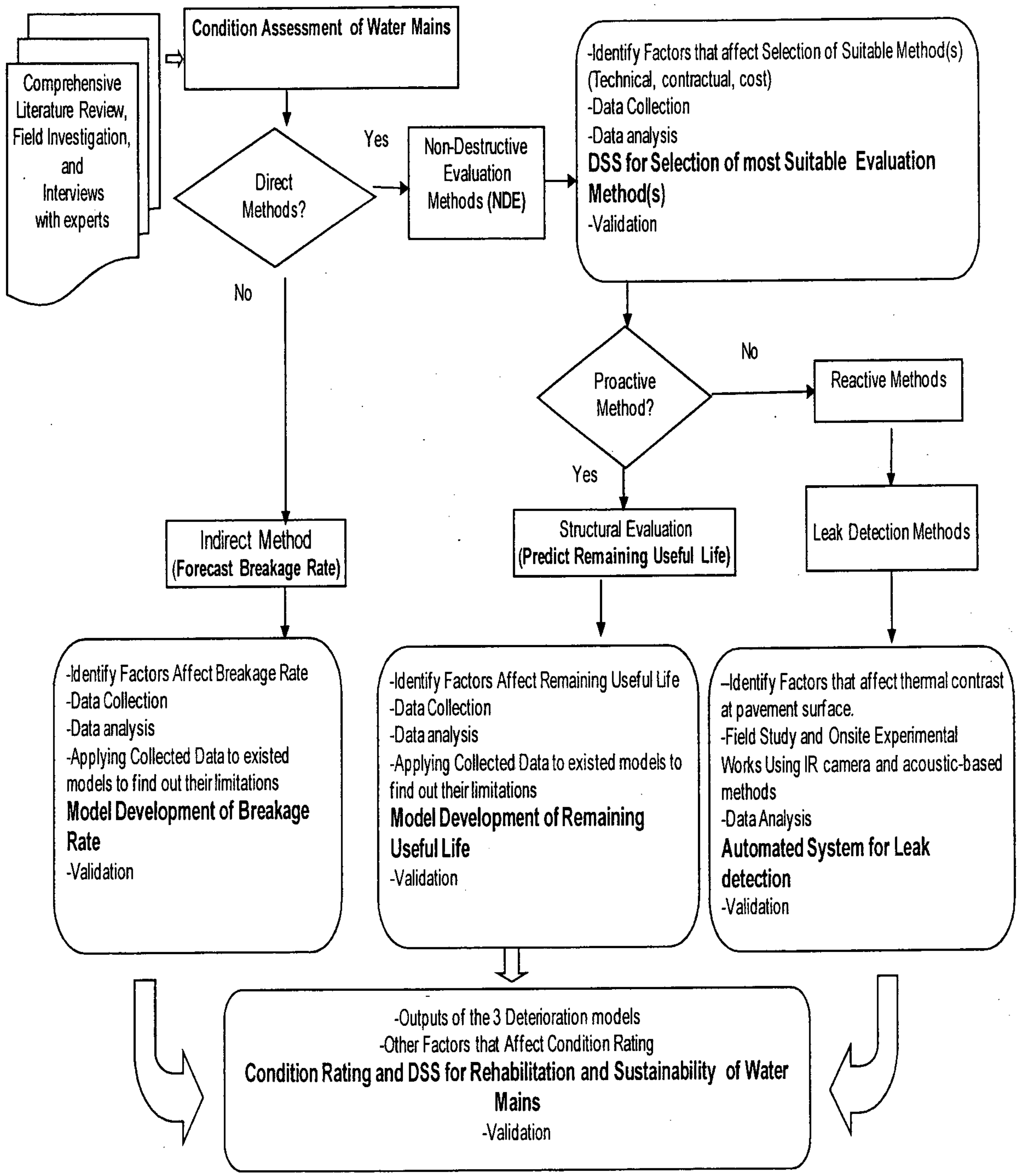


Figure 3-1: Research Methodology

3.3 Interviews with Experts and Data Collection

Sixteen municipalities and practitioners in Canada and the US were contacted in order to gain knowledge and define problems they have faced during planning for condition assessment and rehabilitation of their water main systems. The data collected from these municipalities were used for analysis, define limitations of existing models developed by others, design and develop models in this research, in addition to overall system validation.

3.4 Field Investigation and On-Site Experiments

Field investigation and experimental works were conducted in order to determine the thermal performance and moisture movement of water leaks in underground pipelines, and establish the relationship between the detected leaking areas at pavement surface and the approximate position of the leaks in the pipe being tested.

This study described herein investigated factors that affect the applicability and limitations of using thermography camera for leak detection. These factors include, weather conditions, soil and pavement conditions, ground water level, existence of adjacent sewer pipes and distance of camera from source of leak. In addition, the study also considers the effect of camera setup and the vehicle speed (on which the camera was mounted) on the accuracy of the results obtained.

Three field sites were selected in greater Montreal area, which represent different sets of factors. These sites were located in downtown Montreal, South-West Montreal, and Pierrefonds.

In order to correlate the effects of weather conditions on acquired IR images, the study selected a wide range of weather conditions with varying prevailing light, and ambient air temperature.

3.5 Development of the Methodology

The proposed methodology integrates five newly designed and developed models as shown in Figure 3-1. The development is divided into the following listed phases:

1. Decision Support System (DSS) for selection of most suitable non- destructive evaluation method(s). The design and development of DSS is based on technical, contractual and cost effectiveness factors. It consists of two components: 1) database management system (DBMS); and 2) evaluation and ranking module (ERM). The database is of a relational type, designed and implemented in MS-Access and Visual C# environments, whereas the evaluation and ranking module follows hierarchal in structure and is developed using multi-attributes utility theory (MAUT). This model is flexible to accommodate other methods of inspection as and when they become available.
2. Automated System for detection of water leaks in underground pipelines and identifying their respective locations. The system development involved six major steps: 1) identification of factors that affect thermal contrast at pavement surface; 2) field investigation and on site experimental work; 3) analysis of the data obtained in order to determine the most suitable conditions of using infrared camera IR camera to detect and locate water leaks; 4) establish the results of the relationship between the detected leakage area at pavement surface and the location of leak in the water main being tested; 5) validation of the proposed methodology by comparing the locations of leaks detected by the proposed system with the ones detected by acoustic-based methods, as well as the actual locations detected at the time of repair; and 6) design prototype

software implemented in Visual C# environment in order to determine the location of leaks automatically.

3. Model for forecasting annual breakage rate and model for estimating remaining useful life of water mains, which involved the following five major steps: 1) identify factors affecting deterioration of water mains considering factors beyond those considered in existing models such as external environmental factors in fist model (more details in Chapter 6 and Chapter 7); 2) applying the collected data to existing models to identify their limitations; 3) study the effect of adding important factors beyond those considered in the existing models; 4) develop models based on best subsets of selected factors utilizing neural networks and multiple regression, and then select the model, which best- fit the collected data; and 5) validate the selected model by comparing its results with real case studies.

4. The outputs of the deterioration models developed in this research were used, in addition to the deterioration factors not considered in existing models, as described in Chapter 8, in order to develop a Decision Support system (DSS) for generating condition rating scale of water main being considered, accordingly prioritizing maintenance/ rehabilitation actions. The system recommends maintenance/ rehabilitation actions based on condition rating index of the considered pipeline. The development of this system involved five major steps: 1) identify factors affecting the condition rating of water mains; 2) study the effect of additional important factors beyond those considered in existing models; 3) establish priority index for each factor, and then establish relative weights (i.e. importance) of factors based on pair-wise comparisons; 4)

calculate over all priority index for rehabilitation actions; 5) validate the system by comparing its results with real case studies.

5. The proposed methodology is implemented in prototype software system namely Water Mains Management System (WMMS) as a proof of concept to demonstrate the capabilities and essential features of the developed methodology. The system has been developed using Microsoft Excel and Access, NeuroShell2, and has been coded using Visual C# (C Sharp). In addition, the developed system operates in Microsoft Windows's environment, and is capable of generating graphical as well as tabular reports.

A more detailed description of the methodology of developing the models is given in the following sections.

3.6 DSS for Selection of Suitable Inspection Methods of Water Mains

3.6.1 General

There are essentially two ways to assess the condition of water distribution systems. The first is conducted through direct inspection and monitoring methods that are primarily non-destructive. The second is carried out through collection of data that can be used to generate indirect indicators of the condition (Makar and Chagnon 1999). Non-destructive evaluation (NDE) has certain advantages in detecting problems in pipes over data gathering and statistical methods; in that the latter is approximate and provides more of an overall condition that may not apply to specific sections of the pipe network being analyzed. NDE can detect problems in individual pipes or at a particular point along the length of an individual pipe, providing better information about the condition of such pipes (Makar and Kleiner 2000).

The NDE methods are numerous and are progressively being developed. Current practice of selecting a suitable inspection method lacks the support of a comprehensive database to provide information about the feasibility of using the inspection method in specific conditions, in terms of their capabilities, limitations, and costs. In view of the large number of available inspection methods, selecting the most suitable one without computer-assisted tools can be a challenging task. Most currently used methods are depicted in Figure 3-2. The methods considered utilize technologies; based on acoustics; electromagnetic; visual, thermography, and tracer gas methods.

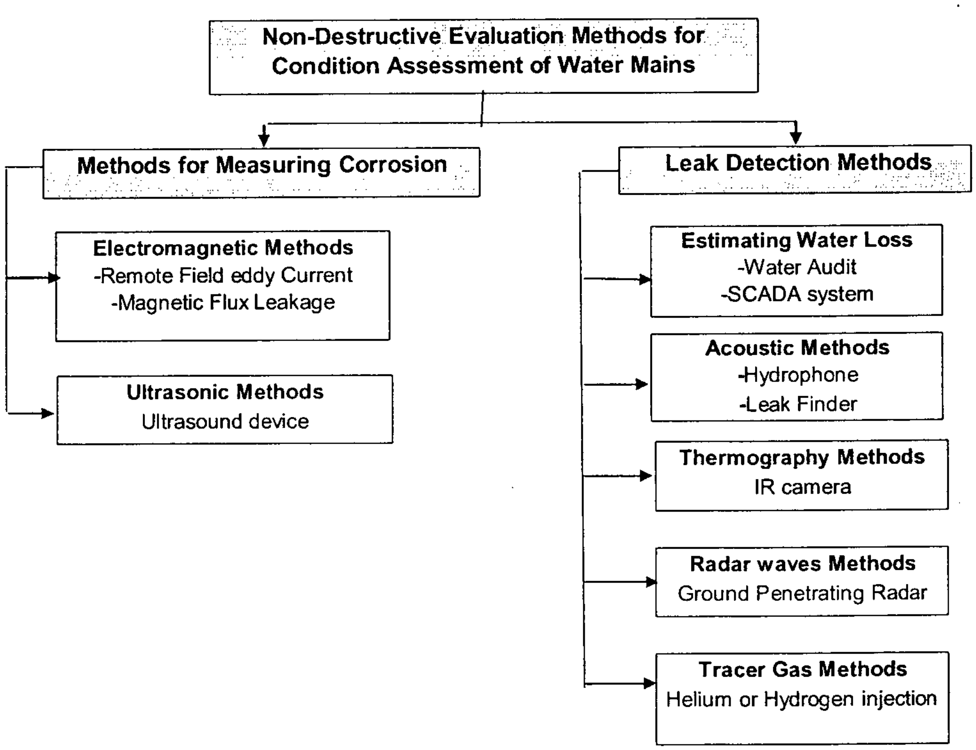


Figure 3-2: Non-Destructive Evaluation Methods of Water Mains

This research presents a Decision Support System (DSS) for selection of most suitable Non-destructive inspection method(s). The system consists of two components: i) database management system (DBMS), and ii) evaluation and ranking module. The system is designed to assist decision-makers in water utilities in selecting most suitable ND inspection method(s). It has a number of interesting features: i) practical and easy to use user-interface; ii) capacity to accommodate different types of commercially available inspection methods; and iii) efficient data representation, storage, sorting, and retrieval. Figure 3-3 illustrates the flow chart of the developed system; each of the system's two components is described below.

3.6.2 Data Base Management System (DBMS)

The developed DBMS is designed to store and retrieve necessary information commonly used in selecting inspection methods for water mains in an interactive manner. A relational database is utilized in the present development. This type of DBMS is most commonly used in engineering applications due to its simple structure that facilitates data updating while allowing a wide variety of users to interact with it (Johnson 1997, Udo-Inyang and Chen 1997, Elmasri and Navathe 2000). The data are organized in tables, each table representing an entity of the developed system, while its columns and rows represent entities' attributes and instants, respectively. These entities (tables) are linked to each other by different types of relationships such as, one-to-many and many-to-many. The design process of the database was carried out in four stages as proposed by Elmasri and Navathe (2000), these stages are: i) data acquisition and analysis; ii) conceptual design; iii) logical design; and iv) physical design. The evaluation and ranking module will be activated only if more than one inspection methods are suggested as shown in Figure 3-3.

3.6.3 Evaluation and Ranking Module

Researchers have developed several mechanisms for problem solving utilizing, in general, a single method of a rigid and static form, insensitive to inherent problem state variation, and problem-solver needs (Moselhi et al. 1992; Moselhi and Hegazy 1993). The developed evaluation and ranking module utilizes the Analytical Hierarchy Process (AHP), and Multiple Attribute Utility theory (MAUT) as shown in Figure 3-3. This methodology proved its effectiveness in comparing alternatives in a multi-attributed decision environment (Moselhi and Martinelli 1990; Moselhi and Sigurdardottir 1998; Shehab-Eldeen and Moselhi 2001and 2002; Al- Aghbar 2005). The methodology combines the advantages of the (AHP) and (MAUT), as described by Marzouk and Moselhi (2003). Details of the system development can be found in Chapter 4.

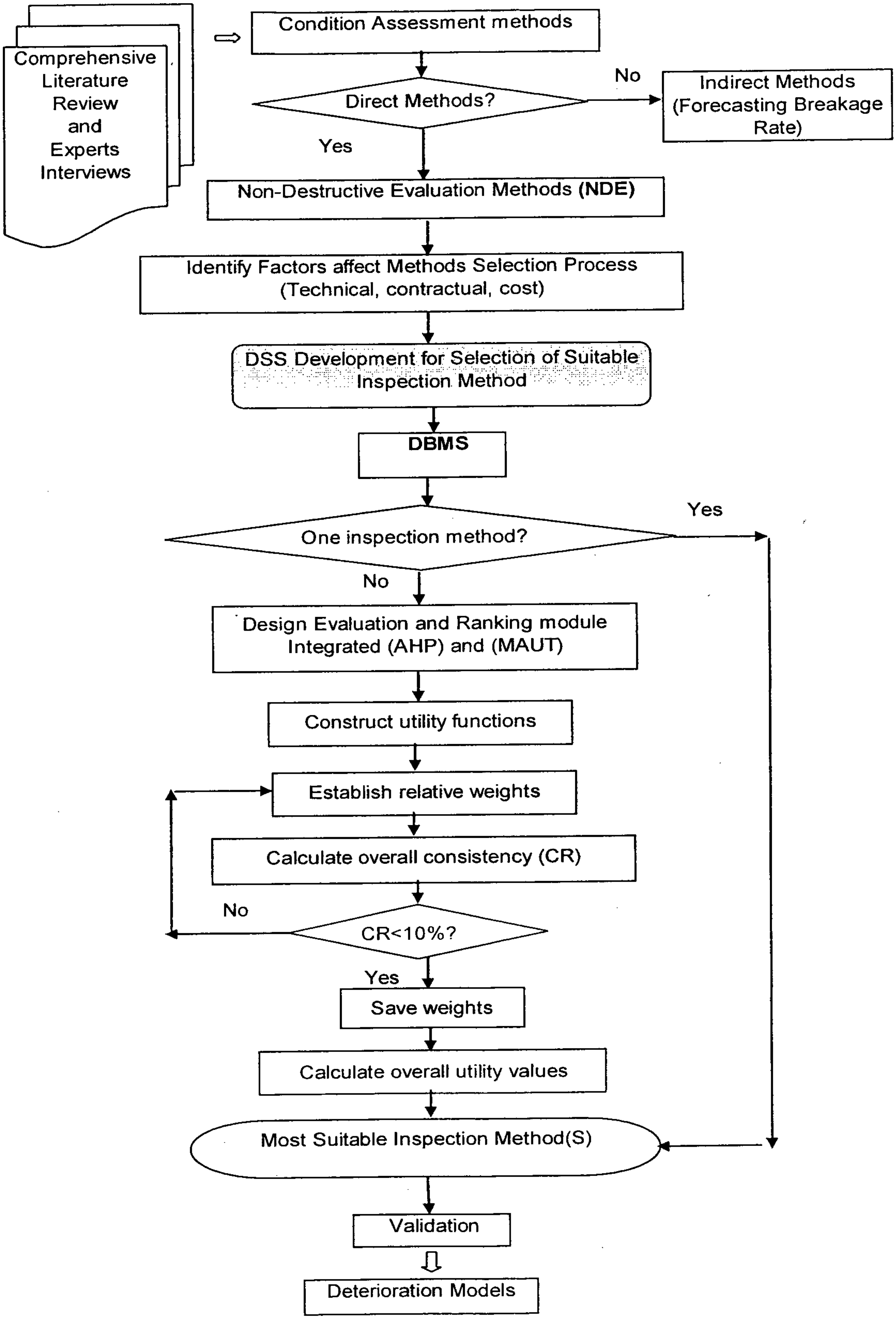


Figure 3-3: Methodology of the Development of the DSS

3.7 Automated System for Detection and Location of Leaks in Water Mains

3.7.1 General

Water systems all over the world experience water losses. Leakage is the most common reason of water loss. Problems associated with water main leaks are a growing concern around the globe. These problems include water and energy loss, in addition to considerable properties damage. In current practice, not all water leaks can be detected due to intensive time and high cost associated with the leak detection process; consequently, some leaks are still occurring and lead to problems mentioned above. Management of water leaks can be improved if leaks can be detected effectively and then rectified efficiently. With enhanced knowledge about the interacting physical processes behind the temperature contrasts at pavement surface due to water leaks, it is possible to improve precision of leaks detection. In such a context, heat and moisture transfer in soil and moisture evaporation from the pavement surface were found to be of particular interest. It should be noted that the use of IR camera for leak detection is not new. Weil (1998) used it in detecting leaks in sewer pipes and identified their respective locations as an affected area rather than a pinpoint location. In addition, he did not provide further details about the most suitable conditions for using the system such as weather condition, camera setup, and speed of vehicle on which the the IR camera was mounted. A study conducted by NRC in collaboration with AWWA to detect water leaks using IR camera (Haunidi et al. 2000), in which they performed thermography survey of a simulated leak area at the NRC leak detection facility during cloudless night in the fall season, but they did not provide details of its capabilities or limitations. However, they recommended further research to study the impact of different site and operating conditions on the effectiveness of that technology.

This present research involves a study conducted to investigate factors besides the ones that have been already considered in previous research. The study also investigates the physical phenomena of heat and moisture transfer in soil due to water leaks and to the benefits of emerging technologies in augmenting current practices in water leak detection, and identify their respective locations in underground pipelines. The research also studied the applicability and limitations of the IR technology employed in the study through field and experimental works using IR camera over two years period in three different locations in greater Montréal (Canada) area. Validation of the proposed model was carried out by comparing the proposed system results (using IR camera) with the results of acoustic-based method and the actual locations of leaks determined during repair.

3.7.2 Methodology of System Development

Extensive literature review, meeting with experts, and on the analysis of actual data collected from three municipalities in greater Montreal area; Pierrefonds, Southwest, and Downtown Montreal (Canada) formed the basis of developing methodology for the proposed system. The development of the methodology involves five major steps: (1) identifying factors that affect thermal contrast at pavement surface; (2) field investigation and on- site experimental work; (3) Data analysis; (4) establish the relationship between the detected leakage area at pavement surface and the location of leak in the water main being tested; and (5) validation of the developed system. These steps are graphically presented in Figure 3-6. Details of system development can be found in Chapter 5.

Factors Affecting Thermal Contrast at Pavement Surface

These factors were identified from the literature review, in addition to actual observation and experimental work carried out in this research. More details about findings can be found in Chapter 5.

Field Investigation and On-Site Experimental Work

The data acquired for the development of the proposed system was collected using:

1- The ThermaCAM S 60 infrared condition monitoring system, which was utilized to conduct a set of field experiments. The system consists of an infrared camera with a built-in 24° lens, a visual color camera, a laser pointer, and infrared communications link (FLIR SYSTEMS 2004). The system was mounted on vehicle to scan a large area in shorter time. This system provides real time high-resolution color images in both infrared and visual modes. The visual mode was used to check the existence of any foreign bodies on the pavement surface, which might affect thermal contrast. To document the thermal variation at pavement surface it is possible to capture and store images on a removable flash card. The captured images with sequential numbers are then analyzed in the field using the developed methodology to determine approximate locations of leaks.

2- Weather data collected from the National Climate Data and Information Achieve http://www.climate.weatheroffice.ec.gc.ca/climateData

3- Temperature of pavement surface, which was measured by IR camera and compared to those measured by thermocouple device. The thermocouple device was also used in measuring soil temperature.

4- Locations of leaks detected by the developed system and those detected by acoustic-based methods (i.e. Hydrophone and the Leak noise correlator), as well as those found during repair.

Data Analysis

The collected data were analyzed in order to determine the most suitable conditions for using IR camera for leak detection and to determine their respective locations. The approximate locations of water leaks were determined based on two major steps:1) determination of areas that indicated thermal change at pavement surface (due to water leaks), and 2) Establish the relationship between detected leaking area and pipe burial depth

Validation of Proposed Methodology

The leak locations detected using IR camera for twenty-five water leaks were compared with those detected using the acoustic-based leak finder method (being the most widely used method in current practice); both records were compared to actual leak locations determined at the time of carrying out the repair work as explained later in Chapter 5. The system layout is shown in Figure 3-4.

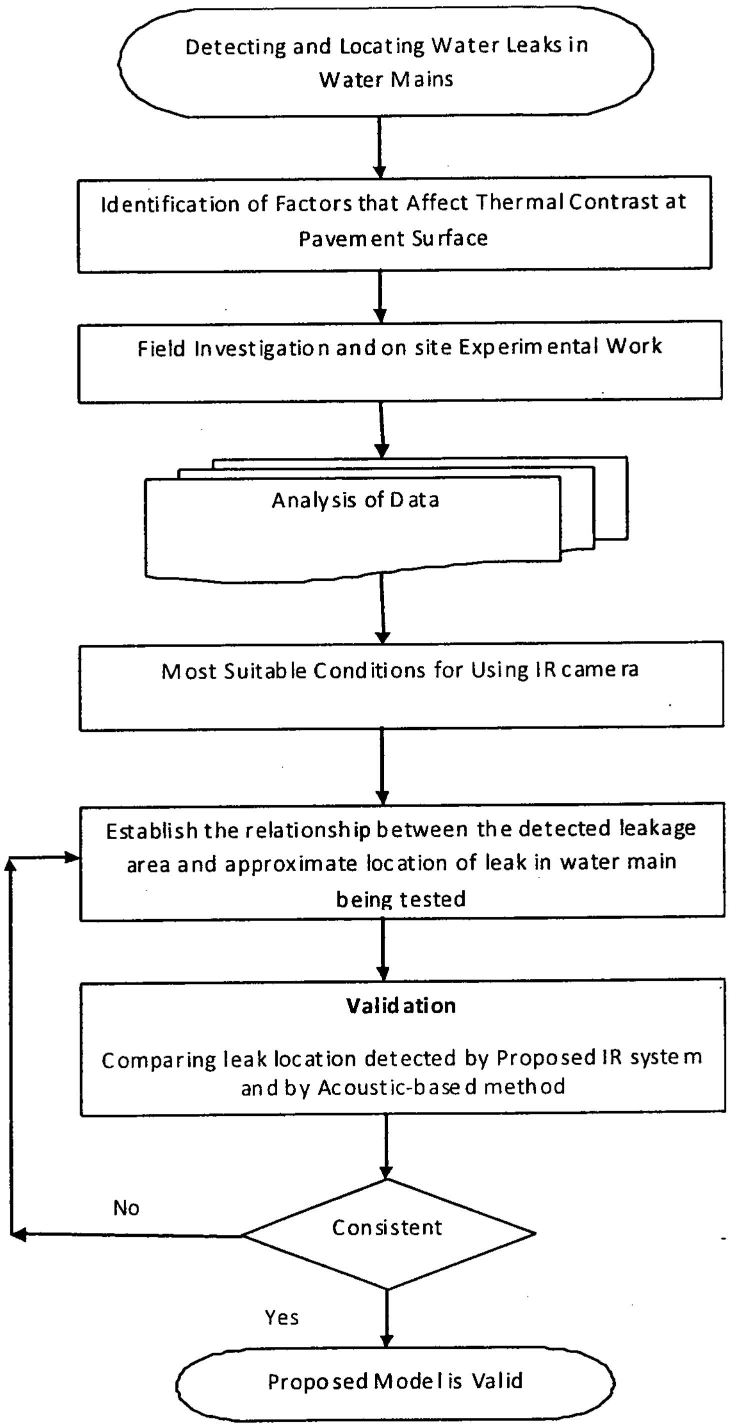


Figure 3-4: Layout of System Development

3.8 Estimating of Remaining Useful Life of CI Water Mains

3.8.1. General

Effective asset management strategy of civil infrastructure systems requires integration of technical and financial plans. This is particularly true in managing water mains, which requires knowledge of their current condition in addition to their forecasted remaining useful life. Ideally, water mains' renewal strategy should exploit to full extent the useful life of individual pipes while addressing issues of safety, reliability, water quality and economic efficiency (Rajani et al. 2000; Rajani and Makar 2000; Seica et al. 2002). As such, efficient asset management programs require reliable estimates of the remaining useful life of the individual assets being considered.

Existing models for estimating remaining useful life of cast iron water mains are primarily based either on characteristics of surrounding soils (Romanoff 1964; Rossum 1969; Gummow 1984; O' Day et al. 1986; Dorn 1996), or on the residual strength of exhumed pipe samples (Rajani et al. 2000; Kleiner and Rajani 2002; Kleiner and Rajani 2004).

This research presents a model designed to forecast remaining useful life of cast iron water mains. The model is easy to use and the generated results are utilized in determining condition rating of the water mains being considered. The output values (remaining useful life) utilized in model development ranged from 0 to 200 years, while, the input variables utilized in model development were selected from intensive study, experts' interviews, and field investigations. This model considers a set of variables beyond those considered in existing models that account for pipe physical properties, mechanical properties, and operational conditions, in addition to the condition of the external environment surrounding the pipe.

3.8.2 Methodology

The data used in model development were acquired from 16 municipalities in Canada and in the US. Three modeling approaches were followed. This includes Multiple-regression model and two artificial neural networks (ANNs): Multi Layer Perceptron (MLP); and General Regression Neural Network (GRNN). Each was used to study the relationship between remaining useful life and a set of deterioration factors, and to forecast the remaining useful life of cast iron water mains. The methodology involved testing each model for significance and accurate representation of the collected data, and then retains the model that out performs the other two (see Figure 3-5). Details of model development can be found in Chapter 6.

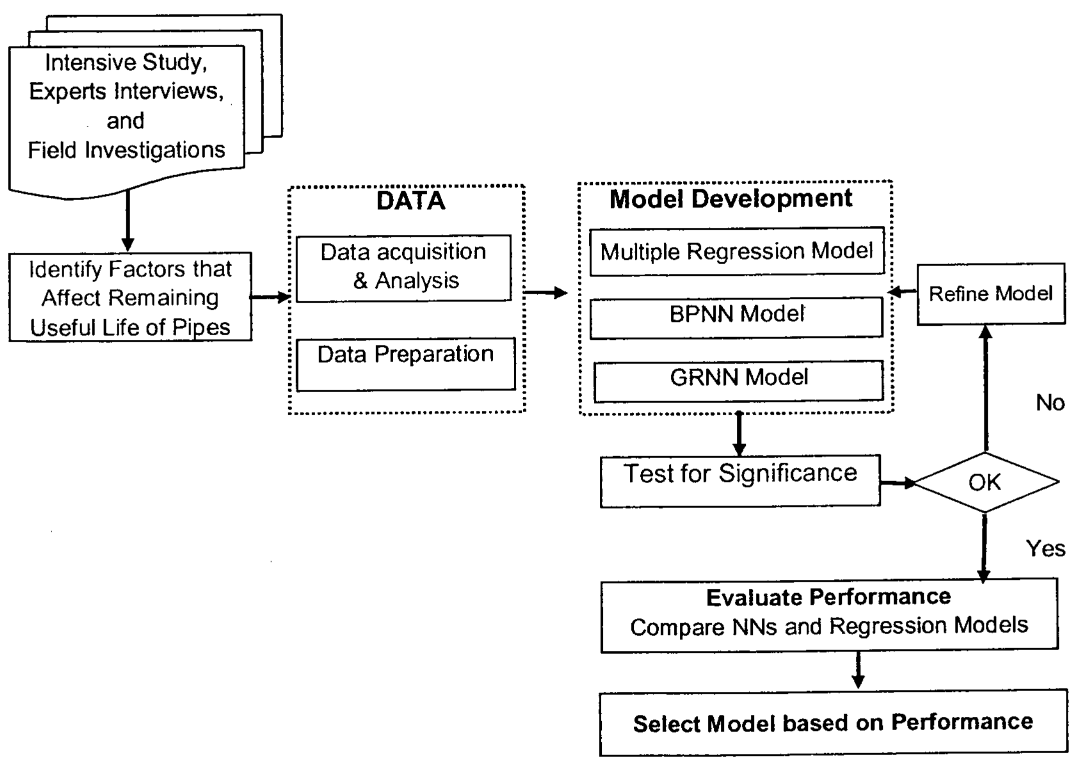


Figure 3-5: Methodology of Remaining Useful Life Model

3.9. Forecasting of Annual Failure Rate of CI Water Mains

3.9.1 General

Since typical water distribution systems comprise hundreds and even thousands of buried pipes, direct inspection of all of them is often prohibitively expensive. Identifying water main breakage patterns over time is an effective and inexpensive alternative to measure the structural deterioration of a water distribution system (Kleiner and Rajani 2000; Kleiner et al 2001). Current practice of using physical or statistical models by many utilities has serious limitations, as presented in a study conducted by (Kleiner and Rajani 2001).

This research presents a model, designed to predict failure rates of water mains. The model is easy to use and the generated results are subsequently utilized in the determination of the condition rating of the pipe(s) being considered. Unlike existing models, the developed model accounts for the external environment that surrounds the pipe as well as the physical characteristics of pipe. Limitations of other existing models can be summarized as follows:

1) Considered only time as dependent variable (Shamir and Howard 1979; Walski and Pelliccia 1982)
2) Clark et al. (1982) have analyzed long pipes (L=792m) considering pipe size, pipe type, water pressure and length of pipe in highly corrosive soil. The correlation coefficient is relatively low (0.23 & 0.45), the low r^2 value corresponding to the linear equation they developed could suggest that this assumption may be incorrect and that the factors affecting deterioration of pipe act jointly rather than independent, and also indicate that other factors affecting time to first break were present but not considered in the equation.

3) Sacluti et al. (1998) applied NN to predict breakage rate based on data collected from Edmonton and include water and ambient temperature, rainfall, operation pressure and historical break records. Their model was applied to a relatively small pipe network and applied to cumulative breaks.

4) Yong Wang (2006) considered pipe age, pipe size and pipe length The correlation coefficient is relatively low (0.68) for the reasons described in (2)

The aim of the presented model herein is to improve model reliability and to apply model to a single pipe as well as a group of pipes. Furthermore, the proposed model accounts for factors beyond those considered in other models described above. It utilizes independent variables, representing pipe characteristics including pipe size, pipe length, pipe age, pipe manufacturing type and external environment such as pipe cover depth, external load, ambient temperature and average precipitation.

Three different data-driven techniques are used to investigate the relationship between failure rates and a set of deterioration parameters, and to predict failure rates of cast iron water mains. This includes multiple-regression model and two artificial neural networks (ANNs): Multi Layer Perceptron (MLP); and General Regression Neural Network (GRNN). A 15-year data set containing routinely measured parameters is used for model development and validation. The data were acquired from Ste-Foy and Laval (Quebec), and Moncton (New Brunswick) municipalities in Canada.

3.9.2 Methodology

Figure 3-6 shows the main activities in the development of the proposed methodology.

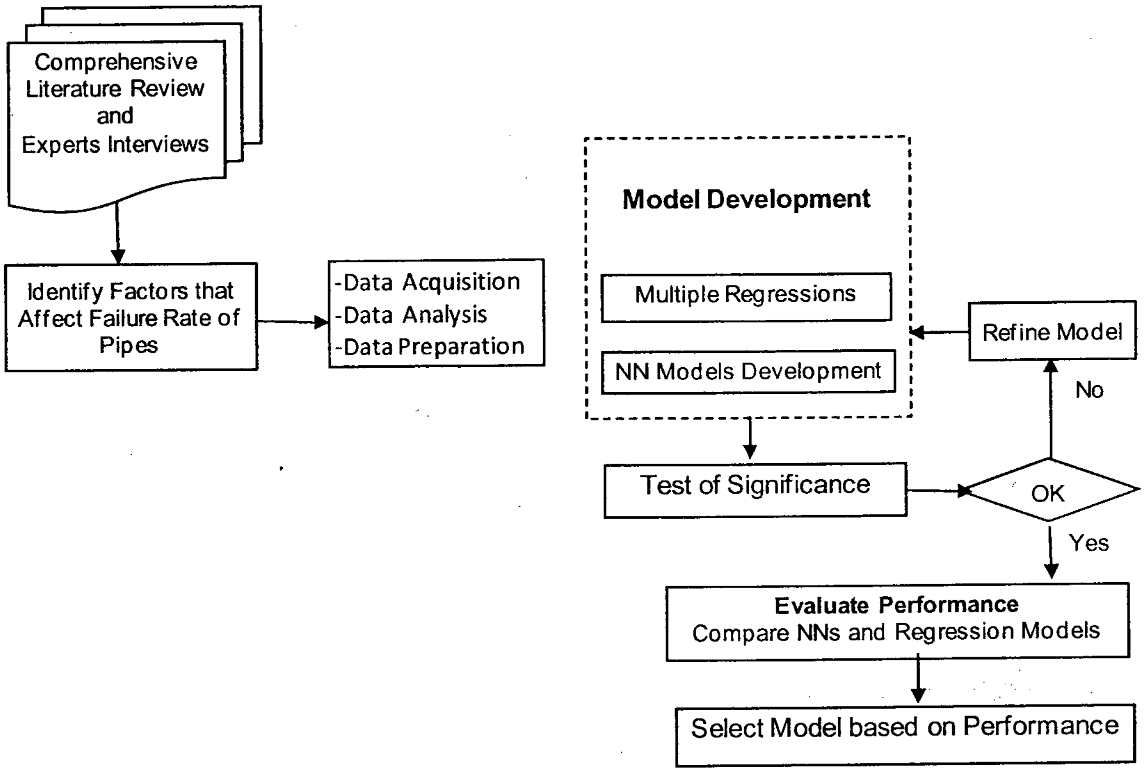


Figure 3- 6: Methodology for Failure Rate Model Development

3.9.3 Modeling Approach

Data-driven modeling approaches are becoming more popular due to the increasing availability of data in the water industry. Water utilities possess large quantities of data derived from control and monitoring facilities. Statistical techniques such as regression analysis can be applied to extract useful relationships from existing data sets, thus making maximum use of the data that are already available (Gibbs et al. 2006). Model development considered two approaches, multiple regression analysis and ANNs. ANNs are used due to their ability to handle nonlinearity and large amounts of data, as well as their fault and noise tolerance. Furthermore, ANNs have the capabilities of learning and then generalization (Lawrence 1994). Two types of ANNs are applied, the Multi-Layer Perceptron (MLP) and the General Regression Neural Network (GRNN). The MLP is the most widely used type of network for forecasting and prediction applications (Maier et al. 2000). Thwin and Quah (2005) revealed that GRNN is a promising technique for building predictive models. Multiple-regression is used as a benchmark, against which the performance of the ANNs can be compared. Details of model development can be found in Chapter 7

3.10 DSS for Prioritizing Maintenance /Rehabilitation Actions of Water Mains

3.10.1 General

As water mains age, deterioration caused by physical, operational, external environment and socioeconomic factors become increasingly significant resulting in a higher frequency of repairs and possibly a reduced hydraulic capacity and water quality. This research presents a study conducted to investigate the impact of physical, operational, socioeconomic, and environmental factors on condition rating of water mains and presents a DSS, which is designed to assist in setting up rehabilitation priorities for cast iron water mains based on a comprehensive condition rating.

The system is of hierarchal structure and was developed using priority index for rehabilitation plans. The development made was based on using the outputs of the deterioration models developed in this research, which is described earlier in this chapter, in addition to deterioration factors that are not considered in already existing models.

3.10.2 System Development

The knowledge gained from experts and from a comprehensive literature review, in addition to the analysis of the collected data was employed in the development of the proposed system. The system was designed and developed in four main stages: 1) Identifying factors that affect the condition rating of water mains; 2) Modeling of condition-rating; and 3) Model validation 4) Incorporating the condition rating model with other deterioration models that were developed in this research in prototype software system to demonstrate the capabilities and essential features of the developed models. The methodology of system development is shown in Figure 3-7. Details of system development can be found in Chapter 8.

3.11 Summary and Concluding Remarks

The study conducted in this research proposes a methodology for condition assessment of water mains and recommends most suitable maintenance/rehabilitation action(s). The methodology integrates newly designed and developed models and sub-systems, which facilitate the decision-making process in managing water utilities, and convey the gained knowledge along with findings to municipal engineers. This chapter outlines the methodology and models developments, while following chapters describe the development of the models and sub-systems in more details.

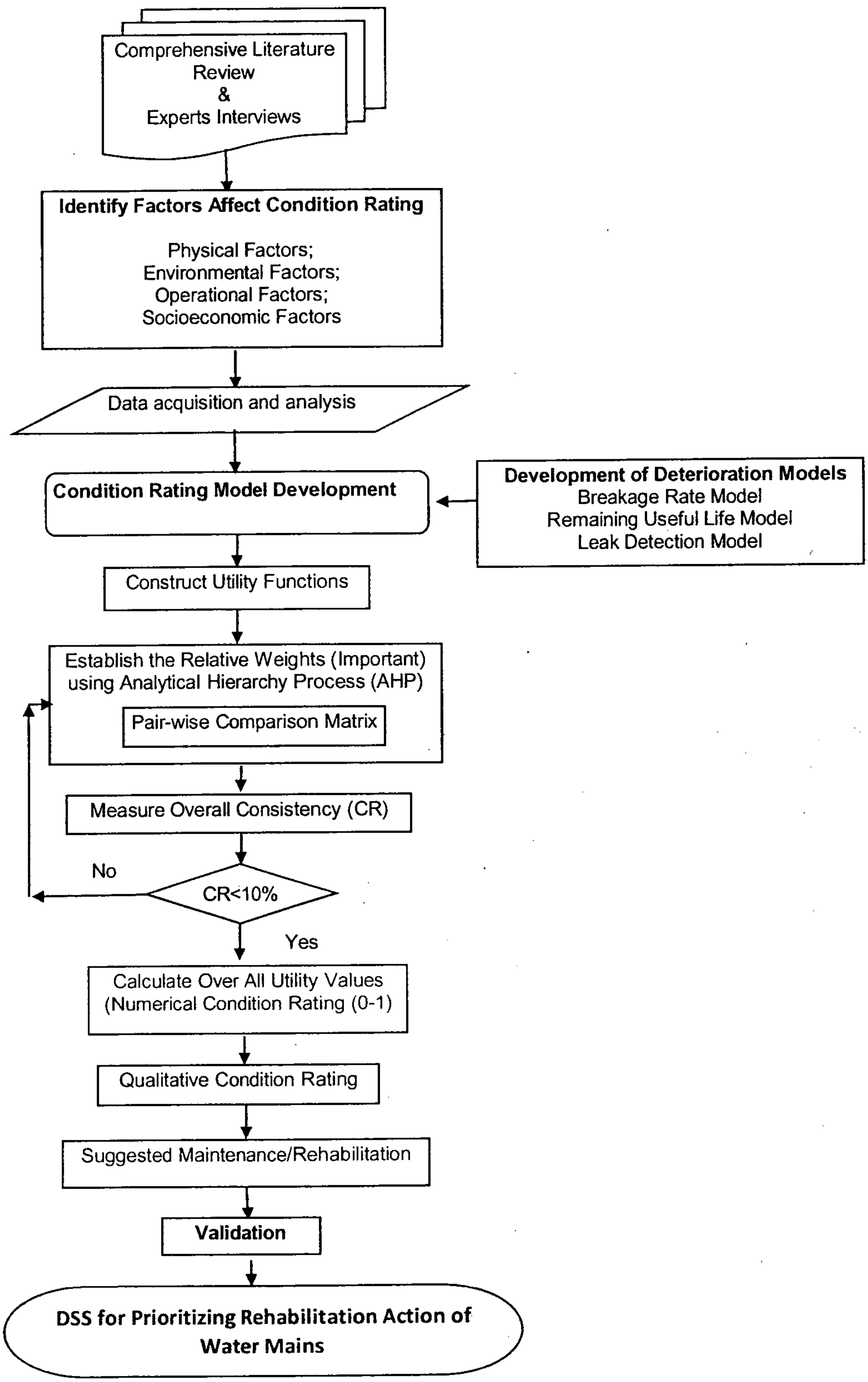


Figure 3.7: Methodology of DSS Development

CHAPTER 4

DSS for Selection of Most Suitable Inspection Methods for Water Mains

4.1General

The design and development of this Decision Support System (DSS) followed the methodology previously described in section 3.6 as depicted in Figure 4-1. The developed system consists of two components: i) database management system (DBMS), and ii) evaluation and ranking module. A detailed description of the system's two components is given below.

4.2 System Design and Development

4.2.1 Data Base Management System (DBMS)

A relational database was utilized in developing the system. The data is organized in tables, each table representing an entity of the developed system, while its columns and rows represent entities' attributes and instants, respectively. These entities (tables) are linked to each other by different types of relationships such as, one-to-many and many-to-many. The design process of the database is carried out in four stages as shown in Figure 4-2, these stages are: i) data acquisition and analysis; ii) conceptual design; iii) logical design; and iv) physical design. These stages are described below.

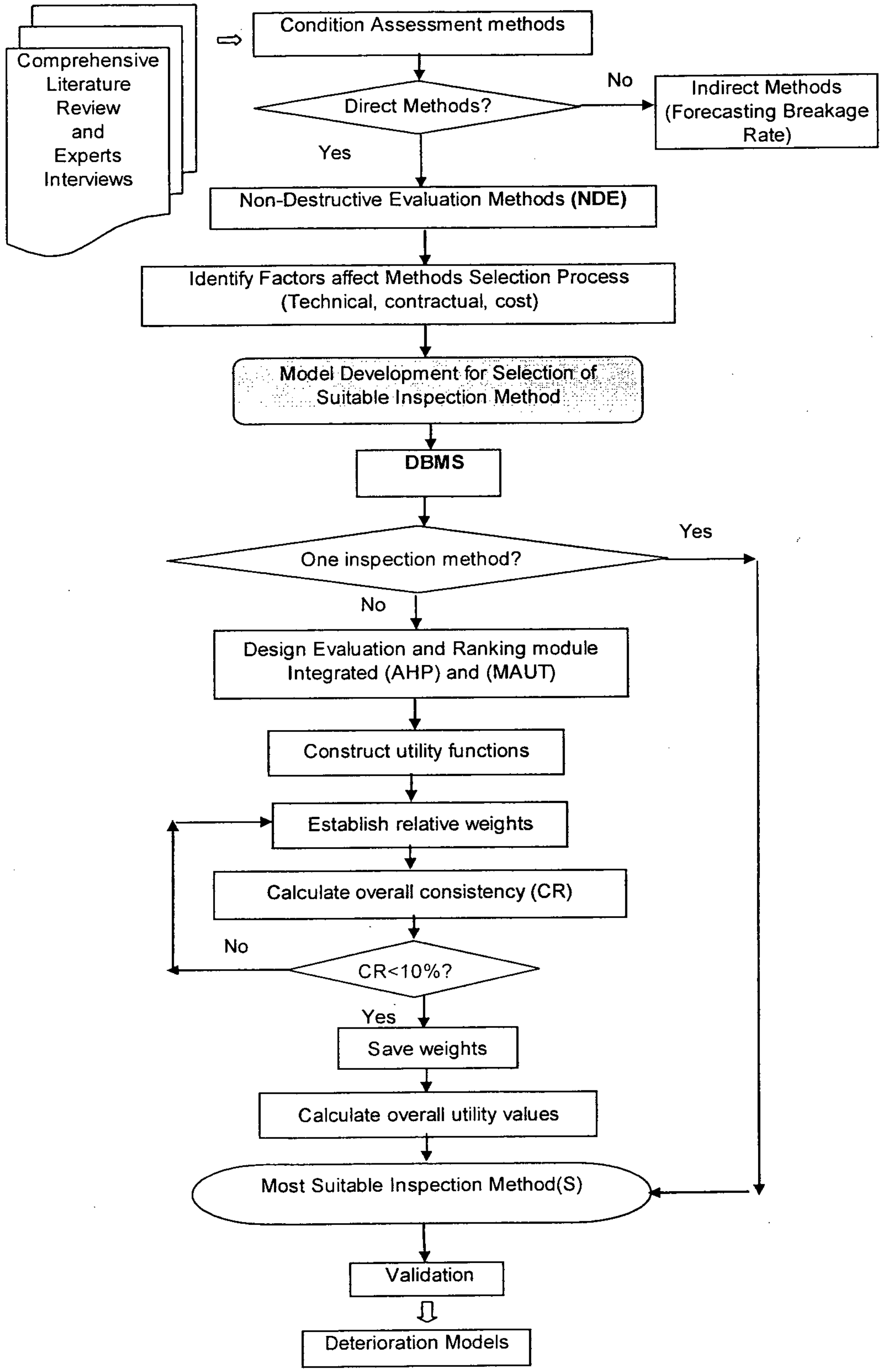


Figure 4-1: Flow Chart for Selection of Inspection Methods

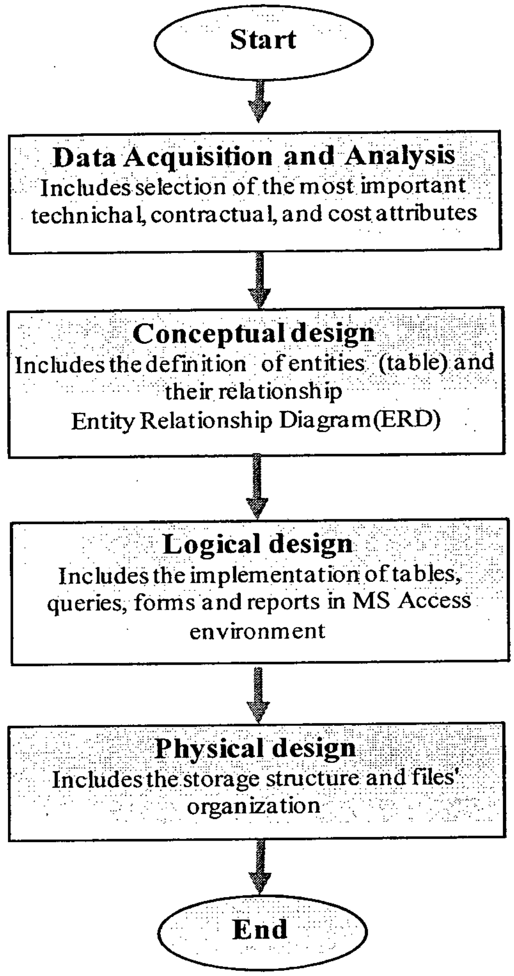


Figure 4-2: Database Management System Design Process

In the data acquisition and analysis stage, knowledge and data were acquired and analyzed through a comprehensive literature review (Makar and Chagnon 1999; Makar and Kleiner 2000; Burn et al. 2001; Eiswirth et al. 2000 and 2001, Hunaidi et al. 1999, 2000, and 2004; Shehab-Eldeen and Moselhi 2001; and National guide (Infraguide) 2003), and interviews with experts (Al-Barqawi 2006, Bourgeois 2006, Loiacono 2006, and Salvo 2006). A Sample of the data used is shown in Appendix B. This research revealed that the selection criteria that affect the decision process for a project depends on three main factors: technical, contractual, and cost effectiveness, which is reinforced by studies carried out by Al-Aghbar and Moselhi (2005). These three main factors account for different attributes according to the type of project being considered.

The knowledge gained from interviews with experts, and comprehensive literature review revealed that technical requirements can be defined as those attributes that determine the feasibility of the inspection method being considered, and are independent of any personal preference or contractual obligations. Technical requirements such as pipe accessibility, pipe material type, pipe diameter, tuberculation condition, weather condition, stray current effect, soil condition, and required measurements accuracy determine the feasibility of the inspection method. Contractual requirements include attributes that ensure compliance of the inspection method with all terms and conditions of the contract. They include inspection duration, bypass requirements, locality of the inspector, and daytime constraints. Cost effectiveness is defined as the ability of the method to fulfill the budgetary limitations of the project being considered and/or to have the least cost among the methods that are found technically feasible and contractually acceptable. These factors and their respective attributes form the decision hierarchy. Table 4-1 depicts the decision criteria used in the developed system.

In the conceptual design, the database is represented by the entity relationship diagram (ERD) shown in Figure 4-3. The ERD provides a comprehensive description of the data structure, specifying attributes and relationships among individual entities. It consists of six main entities: inspection methods, inspection companies, pipe material types, defect type, pipe size, and tuberculation percentage (decrease in inner diameter %). The attributes associated with inspection methods are: method I.D., method name, pipe accessibility, by-pass requirements, stray current effect, soil effect, weather effect, night time constraints, reading accuracy, inspection rate (i.e. inspected length of pipe in m/day), average distance between two successive reading points (i.e. inspection point) and average cost of the method. The attributes associated with inspection companies are: company I.D., company name, contact person, address, phone number, fax number, website address, years in business, locality (i.e. where the company is located) and references to ensure company performance. The attributes associated with pipe material types are types I.D. and pipe types (e.g. Cast Iron). The attributes associated with the type of defects are defect I.D. and defect type. The attributes associated with pipe size (Diameter) are size I.D. and diameter of pipe. The attributes associated to the tuberculation percent are: I.D. and percentage of tuberculation. As depicted in Figure 4-4 the relationships between the inspection methods entity and other entities are many-to-many relationships.

Table 4-1: Decision Criteria and its Attributes

Technical Requirements	Attribute Type	Units / Limits
Pipe accessibility	Text	Yes / No
Type of structural defect	Text	Crack, leak, break, corrosion pit
Pipe type	Text	PVC, CI, DI, PCRC
Pipe diameter	Number	100 (mm)- 450 (mm)
Tuberculation condition	Number	0%-85%
Weather condition effect	Yes/No	Good/Any
Stray currents effect	Yes / No	Yes / No
Soil conditions effects	Yes/No	Dry/Any
Reading accuracy	Number	0.1(mm)- 500 (mm)
Contractual Requirements		
By-pass requirements	Yes/ No	Yes/ No
Locality of inspectors	Yes/ No	Yes/ No
Years in business		2 (yrs) - 20 (yrs)
Day time constrains	Yes/ No	Day time/Any
Inspection rate (Schedule constrain)	Number	m. L / (day) (unlimited)
Cost Effectiveness		
Capital costs of the method	Number	$/ mm of diameter/ m (unlimited)

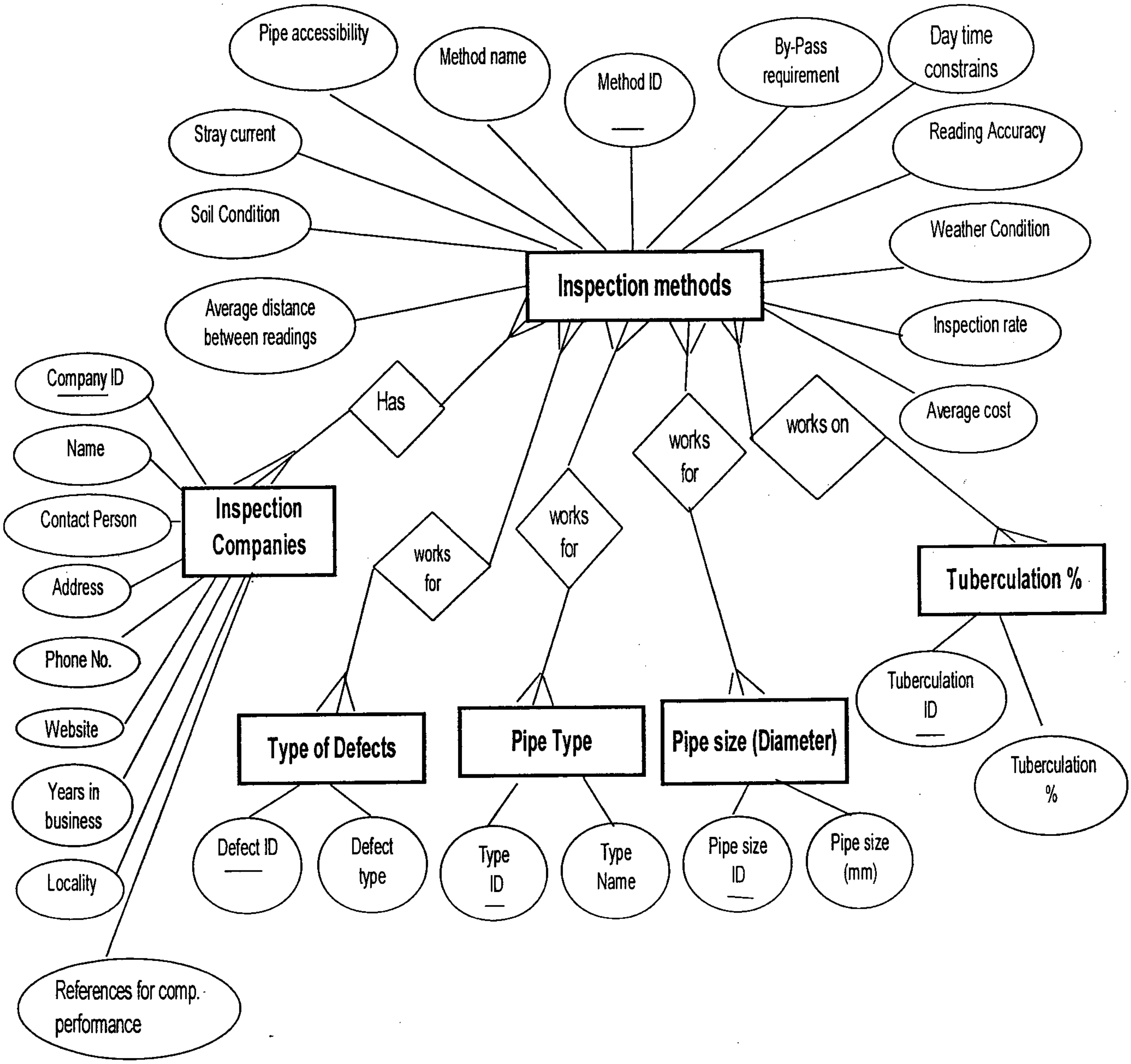


Figure 4-3: Entity Relation Diagram (ERD)

The logical design stage was carried out by constructing tables to represent the entities, establishing relationships among the individual entities, developing queries necessary for data processing and designing user interface forms, which were developed in Microsoft Access and Visual C environments. Figure 4-4 represents a Table. It is an Illustration of the inspection method table in the design view. As can be seen from the figure, it depicts the structure of the table and the associated attributes with detailed description of the types of data. Similarly, all entities and attributes outlined in the ER diagram were mapped into tables; the function of each table is described in Table 4-2. It should be noted that, Microsoft Access does not directly support the many-to-many relationships (Freeman 1997). Therefore, intermediate tables were constructed and connected with the two main tables with many-to-one relationships as shown in Figure 4-5.

In the physical design stage, storage structures and file organization for the database are generated. It should be noted that the developed database system has a flexible design that can accommodate other inspection methods as they become available. The inspection methods used to populate the database designed include acoustic leak finder, magnetic flux leakage, remote field eddy current, ultrasound, and thermography camera.

The evaluation and ranking module will be activated only if more than one inspection methods are suggested as shown in Figures 4-6.

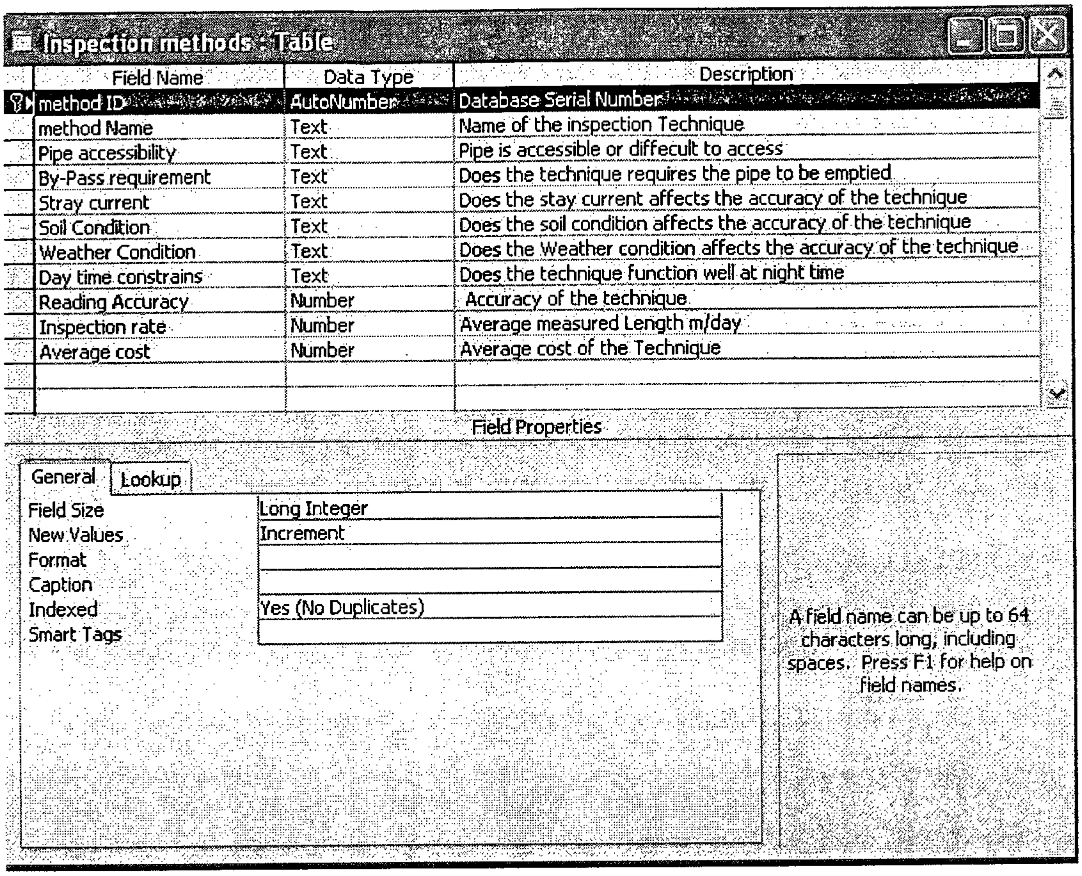


Figure 4-4: Inspection Methods Table in Design View

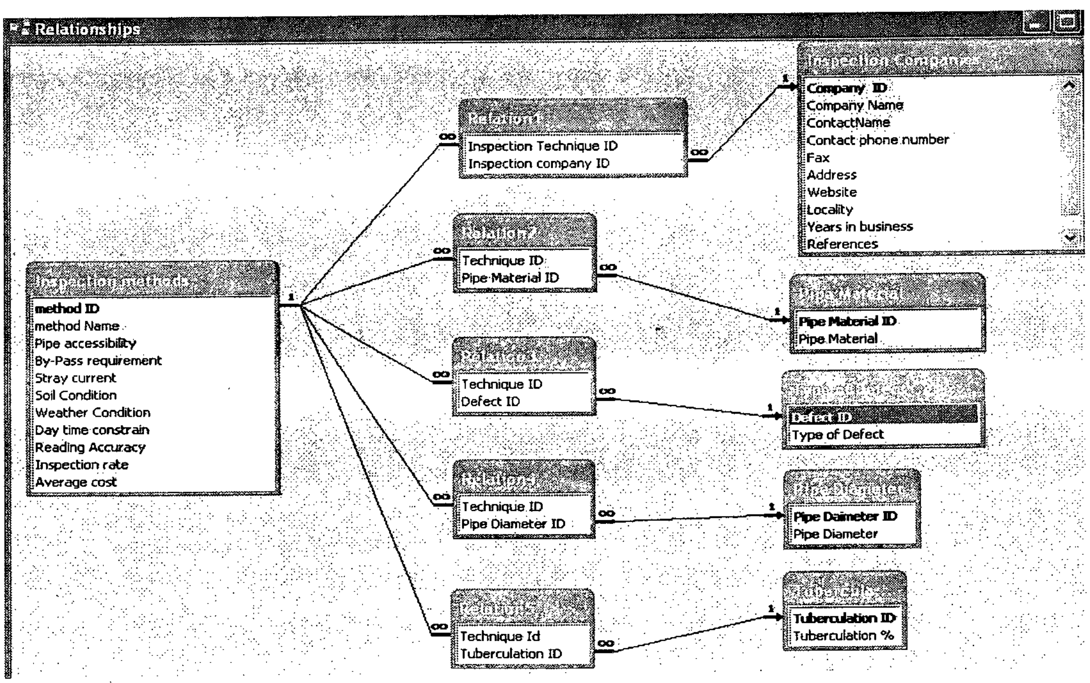


Figure 4-5: Schema of the developed Database

Table 4-2: Description of Various Tables in the Database

Table's Name	Description
Inspection Methods	Contains technical, contractual, and cost information about different inspection methods
Inspection Companies	Contains information about the inspection companies
Pipe Types	Contains different pipe materials that could be inspected by the method
Type of Defects	Contains different types of defects could be assessed by certain method
Pipe size (Diameter)	Contains the range of pipe diameters applicable for certain method
Tuberculation (%)	Contains the range of tuberculation that permits the method to function properly
Relation 1	Connects "Inspection methods" and " Inspection Companies" tables through their primary keys
Relation 2	Connects "Inspection methods" and "Pipe Types" tables through their primary keys
Relation 3	Connects "Inspection methods" and "Type of defects" tables through their primary keys
Relation 4	Connects "Inspection methods" and "Pipe Size (Diameter)" tables through their primary keys
Relation 5	Connects "Inspection methods" and "Tuberculation (%)" tables through their primary keys

4.2.2 Evaluation and Ranking Module

Researchers have developed several mechanisms for problem solving utilizing, in general, a single method of a rigid and static form, insensitive to inherent problem state variation, and problem-solver needs (Moselhi and Hegazy 1992). The developed evaluation and ranking module utilizes the Analytical Hierarchy Process (AHP), and Multiple Attribute Utility theory (MAUT) as shown in Figure 4-7. This methodology proved its effectiveness in comparing alternatives in a multi-attributed decision environment (Moselhi and Martinelli 1990; Moselhi and Sigurdardottir 1998; Shehab-Eldeen and Moselhi 2001; Al- Aghbar 2005). The methodology combines the advantages of the (AHP) and (MAUT), as described by Marzouk and Moselhi (2003).

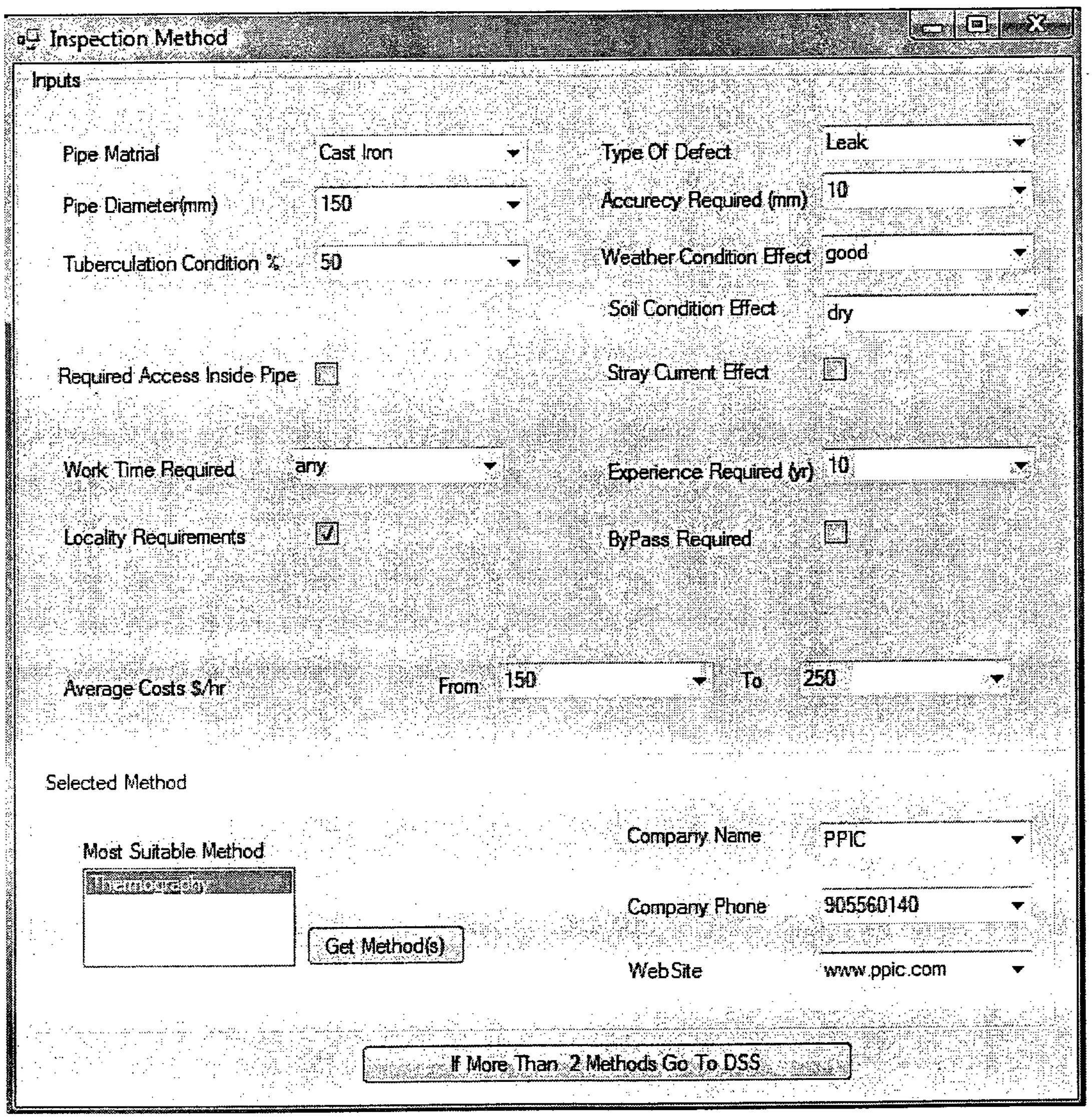


Figure 4-6: Example That Depicts How the Evaluation and Ranking Module Is Induced

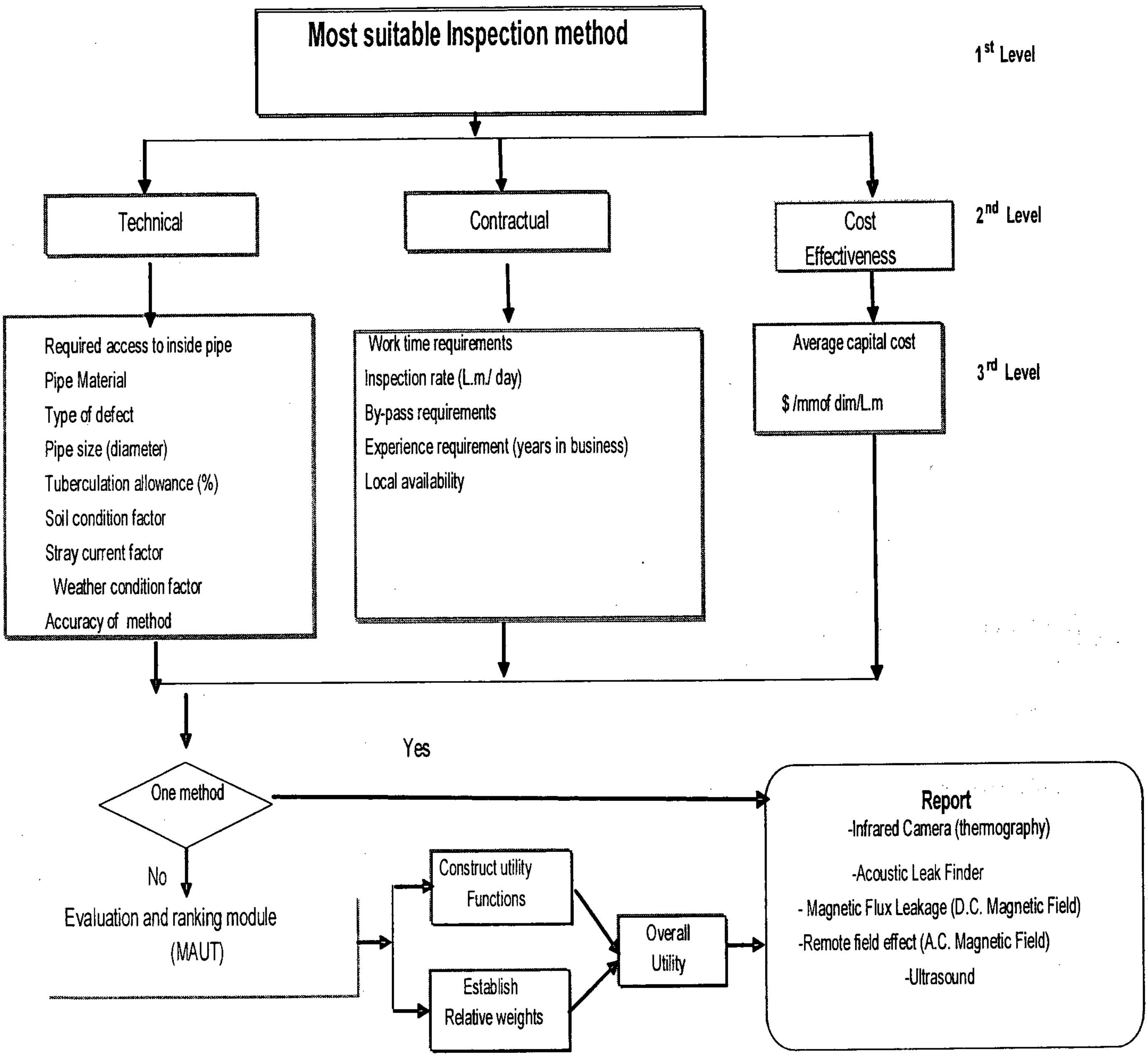


Figure 4-7: Evaluation and Reporting Module

As can be seen from Figure 4-7, the decision hierarchy used in the application of (AHP) consists of three levels providing increasingly detailed definition towards the lowest level (i.e. inspection method). An effort was made in the structure of the hierarchy to insure that the attributes at the lowest level be independent. The user is then required to define a utility function for each attribute, and to assign a relative weight for each attribute. The overall utility value for each competitive alternative can be expressed as:

$$\mathbf{U_i = \sum_{J=1}^{n} W_j \, U_{ij}} \qquad \textbf{(4-1)}$$

Where: U_i = overall utility value of alternative being considered

W_j = the relative weight assigned to the j^{th} attribute

U_{ij} = the value of the j^{th} attribute utility function associated with the i^{th} method of inspection (i.e. the alternative being considered).

Detailed description of the MAUT can be found in Keeney and Raiffa (1993). As shown in Equation (4-1), the first basic parameter is the relative weight (i.e. the relative importance of that attribute among the rest of the attributes being considered). It is determined based on pair-wise comparisons of all attributes as described by Saaty (1982) using a scale of 1-9 as shown in Table 4-3.

The second basic parameter is the utility functions of the attributes being considered, which represent the satisfaction of the decision maker over the range of values on each attribute, which it is expected to have (Moselhi and Martinelli 1990). The utility functions are constructed to express the attitude of the decision maker toward risk and preference (Keeney and Raiffa 1993). In each function the highest utility (i.e. u(x) =100) is assigned to the most desirable value of the corresponding attribute, the lowest utility (i.e. u(x) =0) is assigned to the least desirable value of that attribute as shown in Figure 4-8.

Table 4-3: Pair- wise comparisons (Saaty 19982)

Intensity of Importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favor one activity over another
5	Strong importance	Experience and judgment strongly favor one activity over another
7	Demonstrated importance	An activity dominance demonstrated in practice
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2,4,6,8	For compromise between the above values	To interpolate a compromise judgment

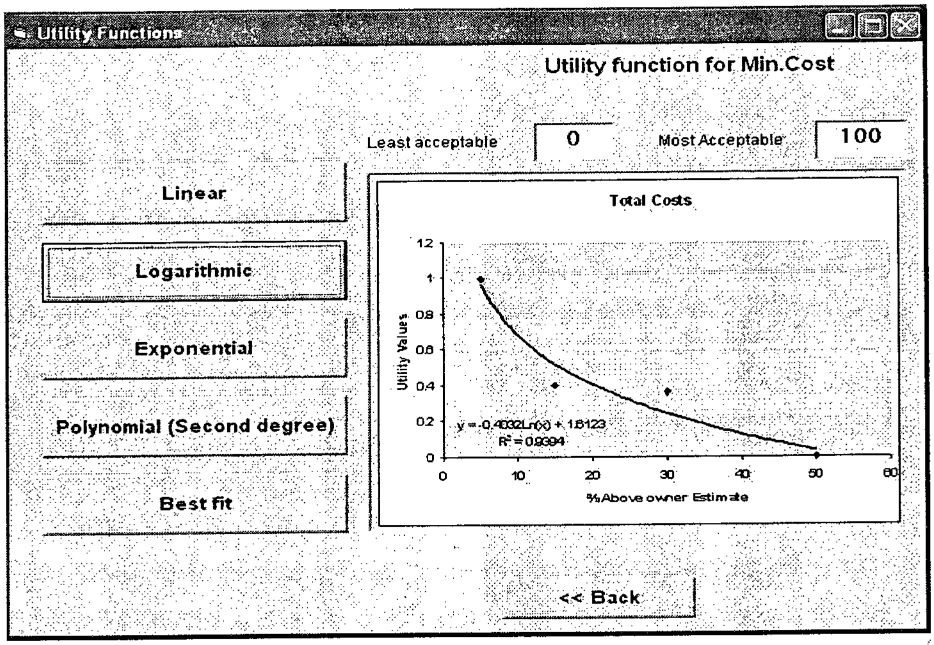


Figure 4-8: Constructing Utility Functions

Upon implementing the utility functions, the system prompts the user to choose between two alternatives. First to use pre-defined weights, which are implemented in the system, and second to reset and establishes the relative weights of the attributes using the analytical hierarchy process based on pair-wise comparison among the various attributes considered as described previously.

To ensure the accurate selection of relative weights, the analytical hierarchy process measures the overall consistency of judgments by means of a consistency ratio as described by Saaty (1982). It should be noted that, the system calculates the **C**onsistency **R**atio automatically. If the CR is less than or equal to 10%, the system prompts the user to the screen shown in Figure 4-10 that gives the user the ranked alternatives associated with its coordinates. If the CR is greater than 10%, the system will prompt the user to revise the relative weights in the pair- wise matrix and repeat the process as shown in Figure 4-9.

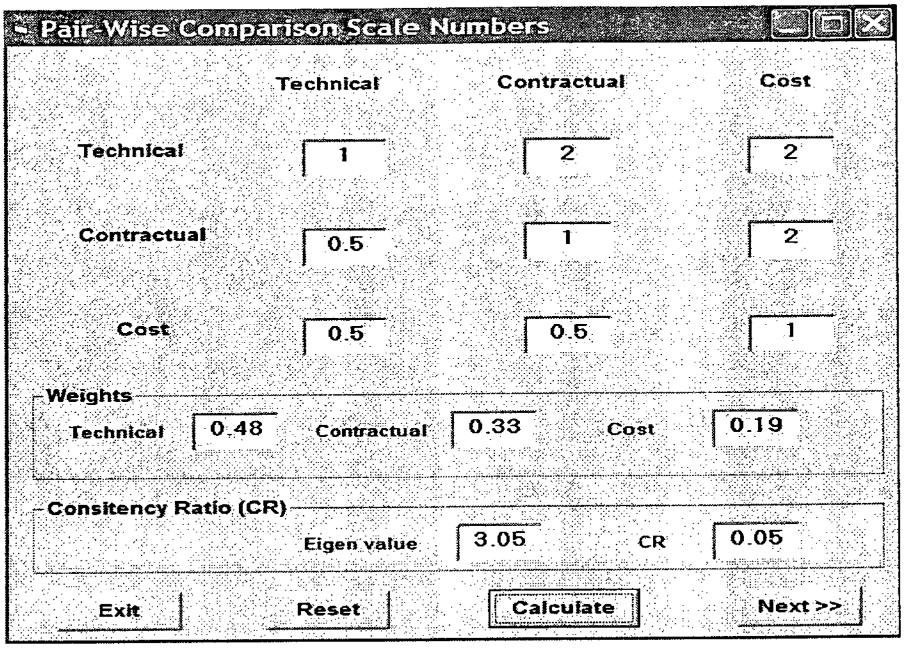


Figure 4-9: Pair-Wise Comparison Screen

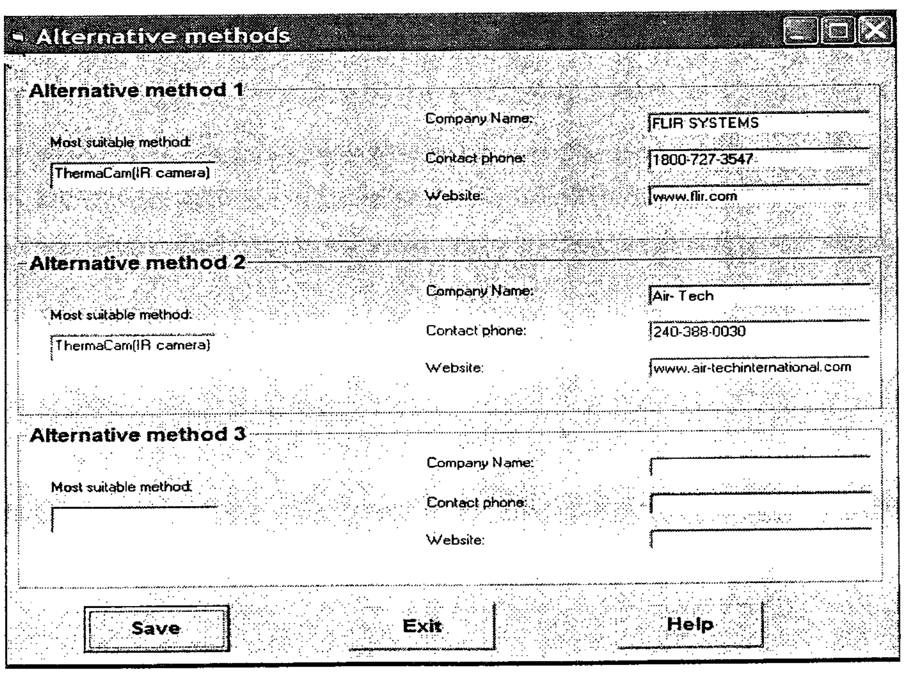


Figure 4-10: Ranking the Alternatives and Their Coordinates

4.3. Relative Significance of Attributes

The study revealed that technical attributes are relatively ranked according to their importance as shown in Figure 4-11, which represents average relative weights derived from relative weights collected from the survey conducted in this research, the results of which are shown in Appendix B; in addition, contractual attributes are relatively ranked according to their importance as shown in Figure 4-12, which also represents average relative weights derived from relative weights collected from the survey conducted (see Appendix B).

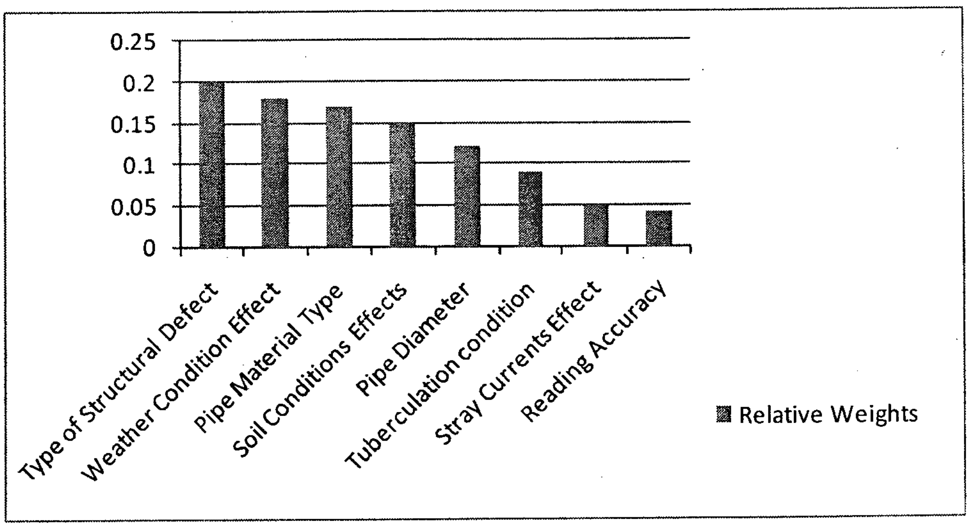


Figure 4-11: Relative Weights for Technical Requirements

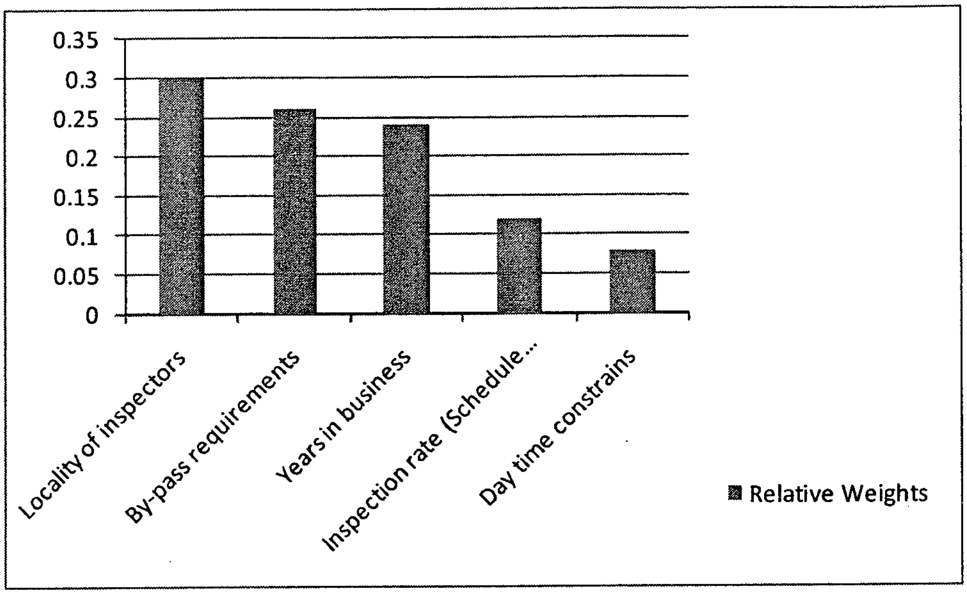


Figure 4-12: Relative Weights for Contractual Requirements

4.4 SUMMARY AND CONCLUDING REMARKS

A Decision Support System for selecting the most suitable Non-Destructive inspection method(s) of water mains is presented. The system consists of two modules 1) data base management system (DBMS) and 2) evaluation and ranking module. The two modules are developed using Microsoft Access and Visual C# environment. Fifteen factors are considered in designing the system. Based on those factors the system can assist users in selecting inspection methods for the water mains, that are technically feasible, contractually acceptable, and cost effective. The study revealed the recommended relative importance of each of those factors. In cases where there is more than one technically feasible and contractually acceptable method, the system triggers its evaluation and ranking module to rank these methods utilizing multi-attribute utility theory (MAUT). An example case study is presented to demonstrate the use and capabilities of the developed system.

CHAPTER 5

Automated Detection and Location of Leaks in Water Mains Using Infrared Photography

5.1 Proposed Methodology

The methodology used in the study involves six major steps: (1) identification of factors affecting thermal contrast at pavement surface, as described in Section 2-4 (Literature review chapter), and from field investigation, explained in the paragraphs that follow ; (2) field investigation and on site experimental work; (3) analysis of the data obtained; (4) determining most suitable conditions for using IR camera in detecting and locating water leaks, (5) establishing a relationship between the detected leakage area at pavement surface and the location of leak in the water main being tested; and (6) validating the proposed methodology by comparing leak locations detected by the proposed system and by acoustic-based methods. These steps are graphically explained in Figure 5-1.

Step1: Factors Affecting Thermal Contrast at Pavement Surface

Through extensive comprehensive literature review, seven experts were interviewed, and preliminary field investigation it became clear that the thermal contrast at the pavement surface is affected by heat balance and heat and moisture transfer in soil.

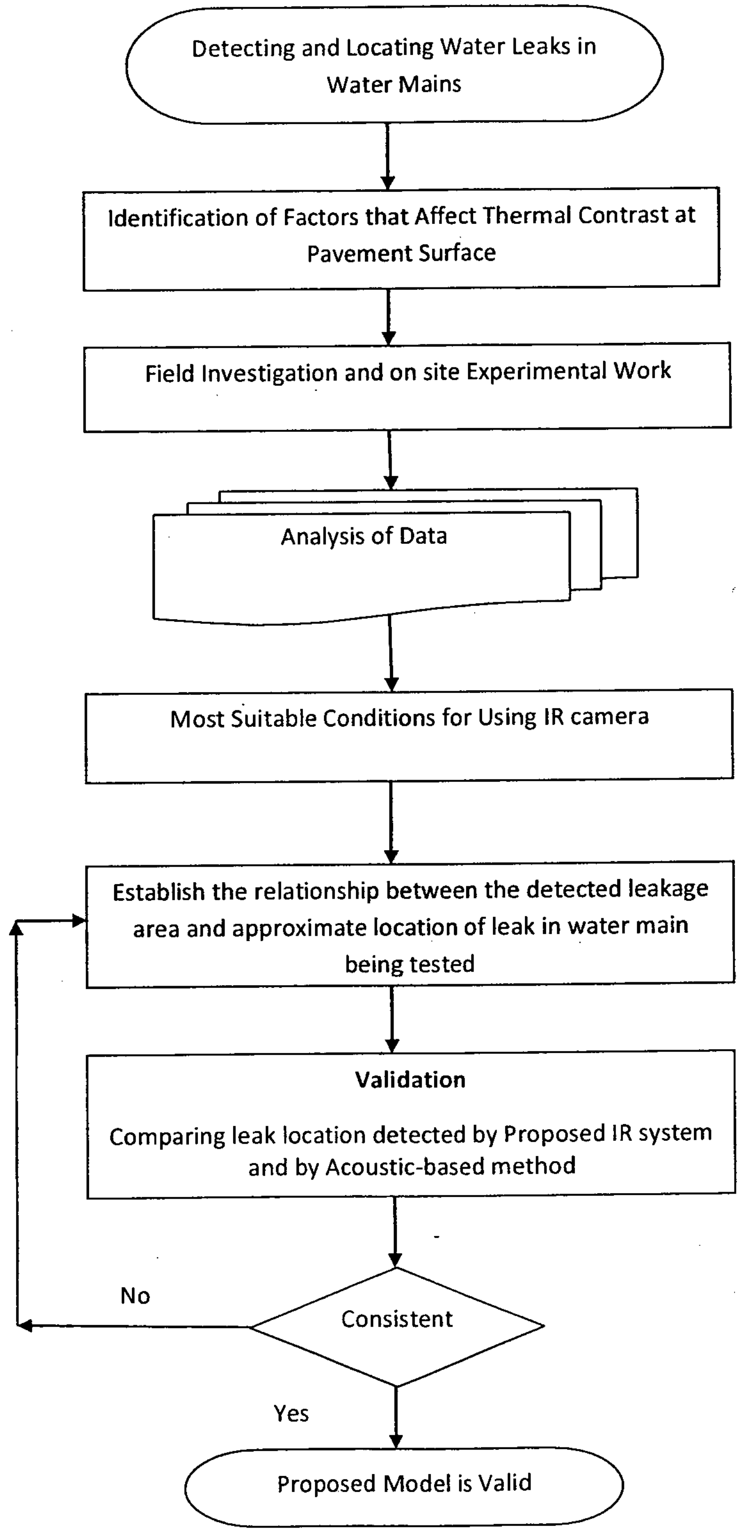


Figure 5-1: Proposed Methodology

At the pavement surface, four modes of heat transfer are considered: conduction into the pavement layer, convection, solar absorption, and grey-body irradiation to the surrounding as declared in more details in the Literature review (Section 2-4). These factors were used to study the effect of weather conditions on the most suitable time to use the proposed IR system.

Step2: Field Investigation and On Site Experimental Work

Field investigation was conducted using thermography IR camera and the results obtained were compared with the results obtained using an acoustic-based system, which will be referred to in this research as "leak finder". The actual leak location was determined while the repair work was being carried (this is normally done within 48 hrs). Leak finder locates water leaks by detecting the sound or vibration induced by water leaking from pressurized pipes. The leak-finder system consists of acoustic sensors such as accelerometers and hydrophones, wireless signal transmitters and receivers, and an electronic processing unit. The sensors are attached at two contact points with the pipe (normally fire hydrants) that bracket a suspected leak. The signals are transmitted from the sensors to the processing unit wirelessly. The processing unit computes the cross-correlation function of the two leak signals to determine the time lag between them. It then calculates the location of the leak based on a simple algebraic relationship between the time lag, sensor-to-sensor spacing, and sound propagation velocity in the pipe (Hunaidi et al. 2004).

Preliminary field experiments showed that the moisture level near the pavement surface affects the pavement surface temperature because of its major influence on the thermal properties of the soil (Fahmy and Moselhi 2009). Furthermore, it was found that the thermal contrast detected by the IR camera was close to the exact location of the leak detected by the acoustic-based leak-finder device. The preliminary survey was followed by detailed field investigation and experimental work to determine the thermal performance of water leaks in underground pipelines, and establish relationship between the detected leakage areas and the accurate location of the leaks.

In order to attain the aforementioned objectives 42 water pipelines were scanned using the IR camera. The diameter of these pipes ranged from 150 mm to 200 mm and their length ranged from 48m to 300 m (see Appendix C). The field tests were conducted in down-town Montreal, South-West Montreal, and the Pierrefonds municipalities in Canada. The present study was carried out over 24-month period from July 2005 to August 2007. The timing of the fieldwork was selected to include a wide range of weather conditions in terms of prevailing light, ambient air temperature, and cloud cover ranging from clear sky to overcast to test the effectiveness of energy transfer between the sky and the pavements studied.

It should be noted that, the average difference in measured temperatures using the IR camera and the thermocouple device was found to be. The average difference in measured temperature was ($\pm$ 2 ^{0} C)

Desired obvious color contrast in acquired images was obtained by adjusting the IR camera set up through number of trials. The distance from the pavement surface to the camera ranged from 1.20 m to 12.0 m. Various combinations of vehicle speed (on which the camera was mounted) and time intervals of capturing images were carried out. The vehicle speed ranged from 5 km/hr to 20 km/hr and the rate of capturing images ranged from image/2 sec to image/10 sec.

Step 3: Analysis of Data Obtained

Average pavement temperature was measured using the IR camera and verified by using thermocouple, while average ambient temperature was taken from official weather website of Quebec as shown in Appendix C, and average temperature of the pipe was measured using thermocouple. The probe of the thermocouple was attached to the end of PVC pipe (2.50 m long) and installed through valve room after removing valve cover. In addition, it was found that the average pipe temperature was the temperature of tap water left running for one minute.

Figures 5-2 through 5-5 show the relationships found between pipe temperature, average ambient air temperature and average pavement temperature. These figures indicate a strong relationship between the average ambient air temperatures and the observed pavement surface temperatures. According to Equation 2-1 (Refer Literature Review chapter) the heat transfer occur from the higher temperature surface (e.g. pipe temperature in winter) to lower temperature surface (e.g. pavement surface in winter). Thus, there is a high possibility of detecting water leaks using the IR camera from week number 1 (i.e. first week of January) to week number 22 (i.e. first week of June), and also from week number 42 (i.e. middle of October) to week number 52 (i.e. end of December), as shown in Figures 5-2, 5-3, and 5-5. These findings indicate that weather has a considerable effect on the limitations of using the camera and it is recommended to use the system in locations with dry and moderate weather conditions

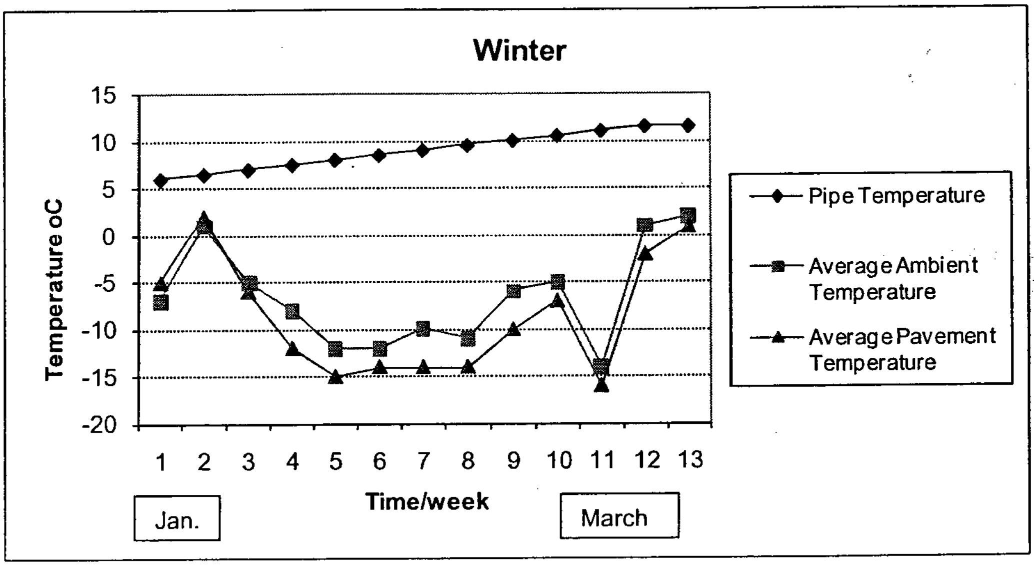


Figure 5-2: Comparison between Temperatures in Winter Season

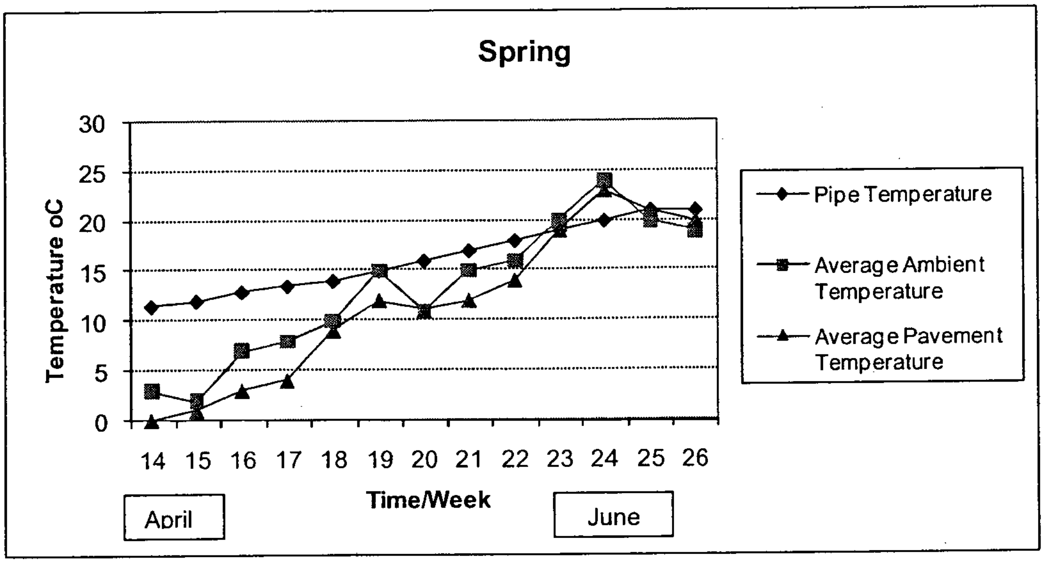


Figure 5-3: Comparison between Temperatures in Spring Season

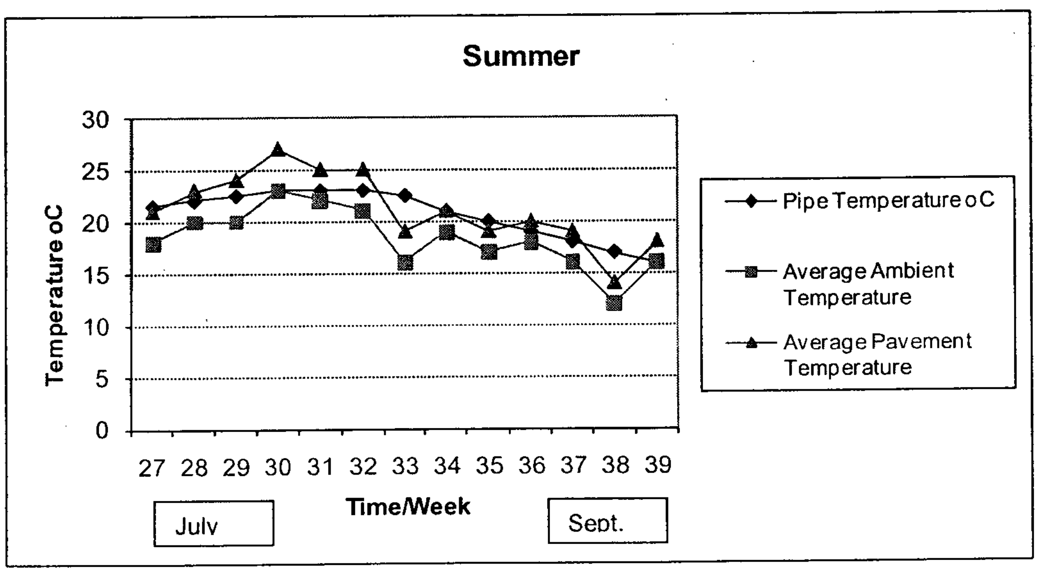


Figure 5-4: Comparison between Temperatures in Summer Season

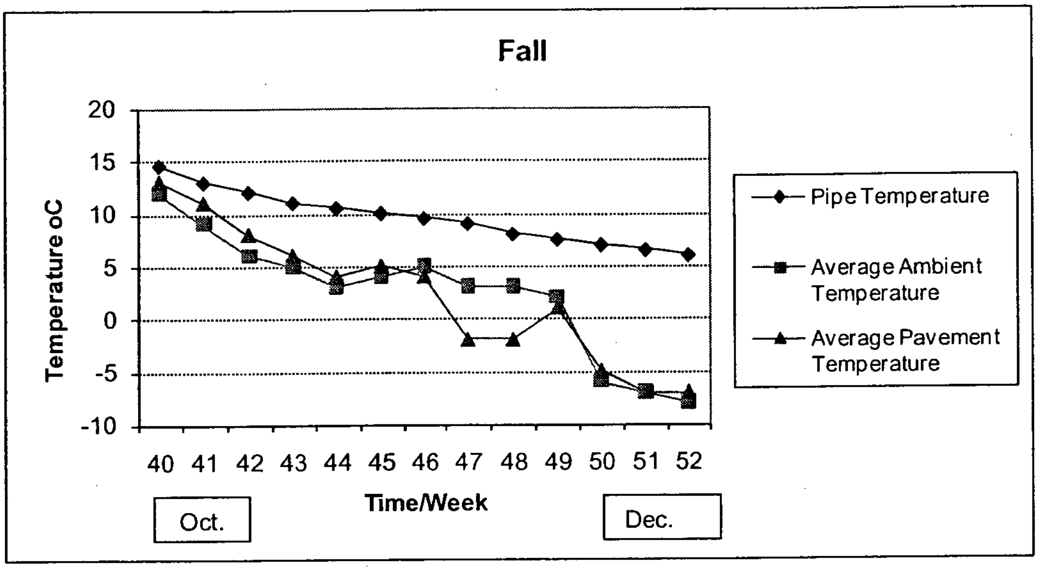


Figure 5-5: Comparison between Temperatures in Fall Season

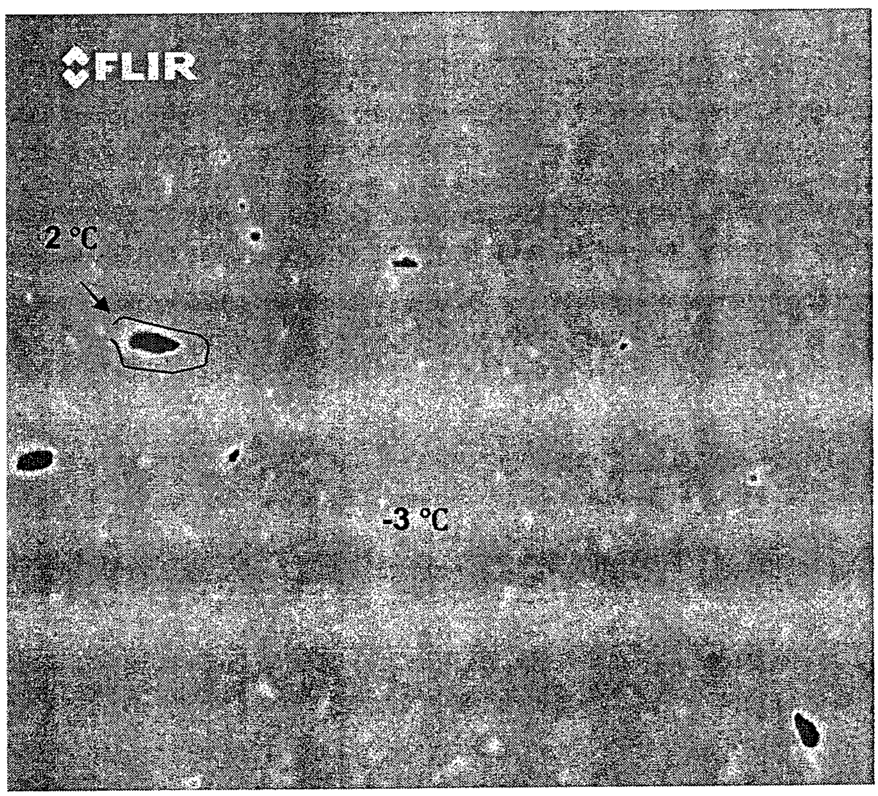


Figure 5-6: Water Leak Detected in Winter

As shown in Figure 5-6 the thermal contrast identified at the pavement surface due to water leaks is hardly interpretable in winter due to the smaller area resulting from freezing of the upper layer of soil up to a depth of 1.80 m. On the other hand, during the Fall season, as shown in Figure 5-7 the thermal contrast is quite clear and easily interpretable.

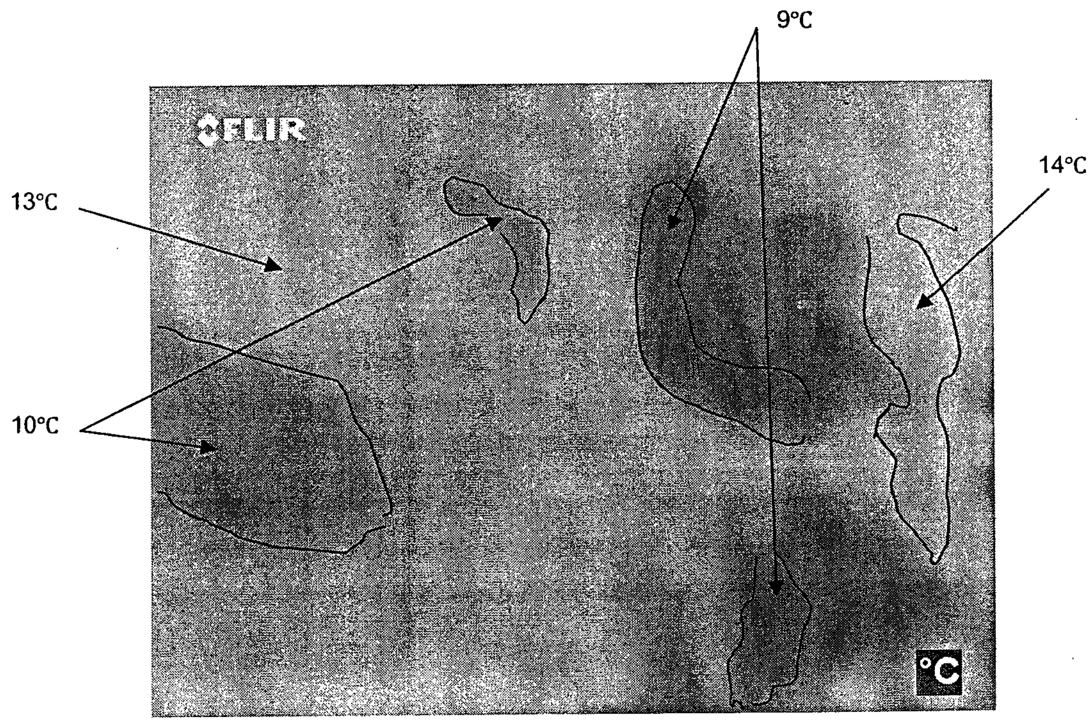


Figure 5-7: Water Leak Detected in Fall

Step 4: Determining Most Suitable Conditions for Using the Proposed System

a) Cloud Cover and Prevailing Light

Data collected during this research showed that pavement temperatures under clear sky and/or during daytime were consistently warmer than pavement temperatures under cloudy condition and/or at night and early morning. As a result, heat and moisture flow towards pavement surface generated from leak in warmer pipe will be decreased; consequently, detection of leaks will be more accurate under overcast condition between 11 pm and 6 am. Table 5-1 shows a sample of average daily temperatures recorded on the 30th of September 2007.

Table 5-1 Average Daily Temperature on 30th of September 2007

Time	Ambient Temperature	Pavement Temperature	Pipe Temperature
0:00	14.4	16	16.8
1:00	14.4	15.3	16.7
2:00	13.7	15.1	16.7
3:00	12.3	14.9	16.6
4:00	12.5	14.8	16.6
5:00	12.5	14.7	16.5
6:00	12.8	14.8	16.5
7:00	13.2	15	16.6
8:00	14.6	16.5	16.7
9:00	15.6	17.8	16.8
10:00	17	19	17
11:00	19	21.5	17.1
12:00	19.6	22.3	17.2
13:00	19.9	23	17.3
14:00	20.5	24.8	17.5
15:00	20.5	25	17.4
16:00	19.5	24.8	17.4
17:00	18.1	24	17.3
18:00	17	22.5	17.3
19:00	16.8	21.5	17.2
20:00	16.7	20.2	17.2
21:00	16.6	19.1	17.1
22:00	15.5	17.9	17.1
23:00	14.7	16.8	16.8

b) Changes in Thermal Characteristics of Soil and Pavement Surface

Soils close to water leaks experience increase in moisture content and may become saturated. Such change in moisture content changes the thermal characteristics of the soil and makes it more conductive to heat relative to dry soil away from the leak. The soil temperature variation observed in this research through the four seasons indicates that the soil temperature variation is higher in shallow regions than in deeper depth. During summer, the temperature difference at pavement surface between summer and winter was 38 °C, which decreased to about 14 °C at the depth of 1.00 m, and further decreased to approximately 2 °C at the depth of 1.80 (the average depth of water mains). During winter (see sample in Appendix C), the average soil temperature of deeper layers is higher than that at the shallow soil depths. It means that during winter the heat is transferred from the deeper soil depths to surface, wherease during the summer months a reverse flow is observed, which is in agreement with the recent study conducted by Antonopoulos (2006). Also during winter, the rate of change in soil temperature under snow cover was less due to low thermal diffusivity and high albedo of snow. It was also found that the detected water leaking areas had a thermal contrast at pavement surface that decreased with soil surface evaporation during daytime and slightly increased during nighttime.

C) Infiltration Into Adjacent Sewer Pipes

The field investigation and experimental work carried out in this research revealed that more than 40% of the water leaks detected (15 leaks out of 40) were infiltrated into adjacent defected sewer pipes, thus preventing the moisture movement from reaching the pavement surface, thereby making it difficult for the IR camera to detect such leaks.

D) Ground Water Table

The ground water table greatly influences the use of IR camera as evidenced through the experimental work conducted in the vicinity of Saint Laurence River in Montreal. The ground water table of the studied area was higher than the pipe level. The IR images captured to the pavement surface in this area showed no variation in the thermal properties of the pavement surface.

E) **Distance of Sensor from Source**

The impact of distance between the pavement surface and the camera was studied. Tests were conducted over a distance ranging from 1.20 m to 12.0 m. using the basic components of the camera (i.e. built in 24^{o}). Field experiments revealed that the average diameter of the detected leaks at the pavement surface ranged from 3.0 m to 6.75 m as shown in Figure 5-8. Thus, increasing distance between the pavement and the sensor provided better and accurate diameter of detected leaks (Refer Table 5-2).

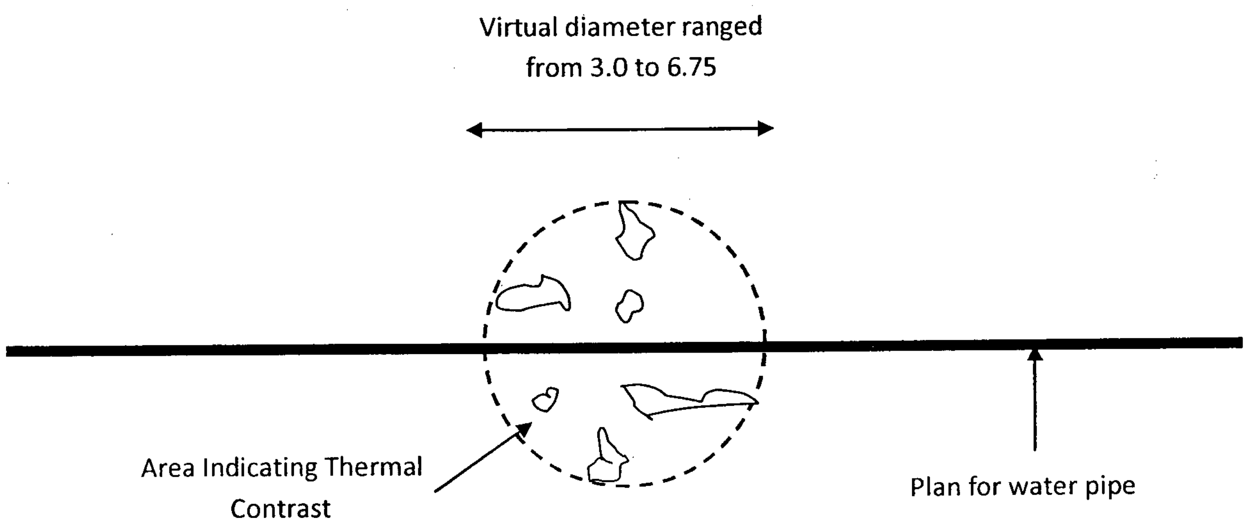


Figure 5-8: Water Leak Indicating Thermal Contrast at Pavement Surface

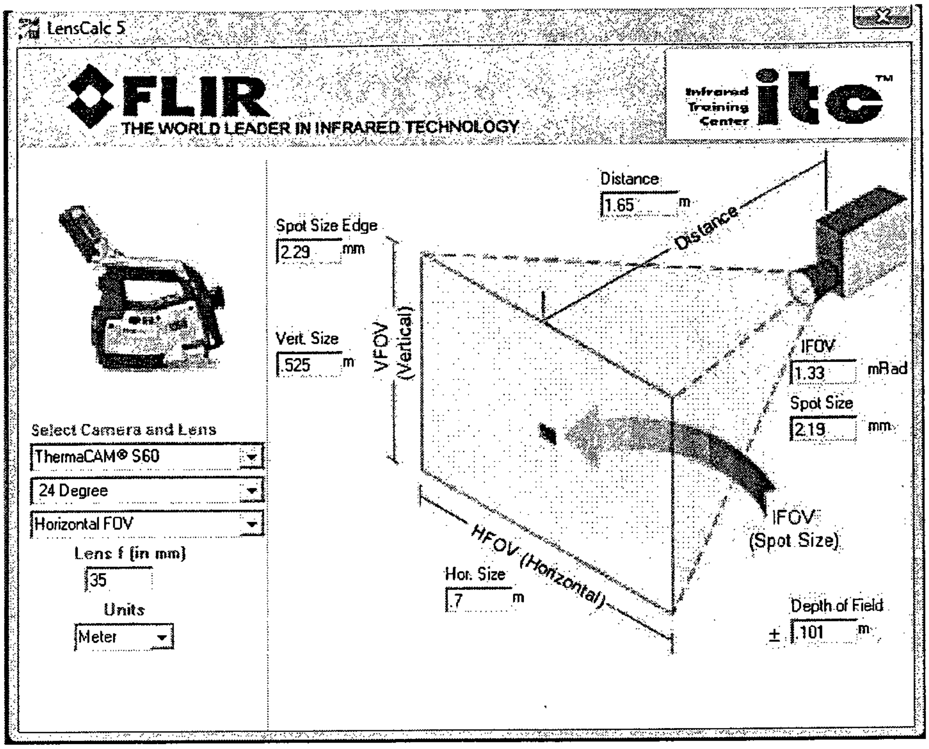


Figure 5-9: Area Detected Using 24° Lens/ 1.65 m Distance

It should be noted that using accessories such lens with 45° or 80° reduces the distance required for defining area-indicating leak at the pavement surface, facilitating better control of the system, as shown in Figure 5-9 and Table 5-2.

Table 5-2: Effect of Lens Angle on the Relation between FOV and Distance from IR Camera to Pavement

Lens	Distance from Pavement to IR Camera	Vertical Field of View	Horizontal Field of View
24°	12 m	3.80 m	5.10 m
24°	15.88 m	5.06 m	6.75 m
45 °	6.12 m	3.80 m	5.10 m
45 °	8.15 m	5.06 m	6.75 m
80°	3.04 m	3.80 m	5.10 m
80°	4.02 m	5.06 m	6.75 m

F) Vehicle Speed and Rate of Capturing Images

Various combinations (12 sets) of vehicle speed (ranging from 5 km/hr to 20 km/hr) and rate of periodic capturing of images (image/2 sec to image/10 sec) were experimented to understand the relationship between the two. The results obtained showed the optimal vehicle speed to be 5 km/hr and the optimal rate of capturing images to be image/2 sec as shown in Figure 5-10.

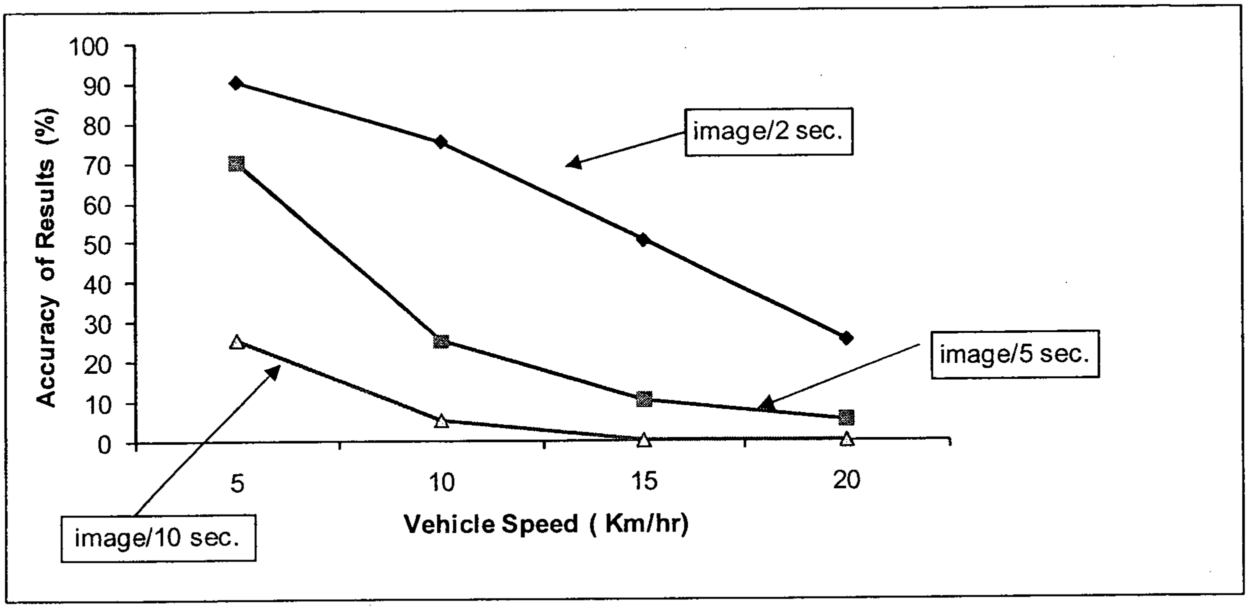


Figure 5-10: Relationship between Vehicle Speed and Accuracy of Results

G) Effect of IR Camera Setup

In order to obtain obvious color contrast in acquired images, camera set up was adjusted based on sets of thirty-six trials. The most effective parameters were found to be emissivity, palette type, and noise reduction function that reduce clutters. These parameters were set with the following values:

-*Emissivity* was set based on pavement status ranged from 0.85 for snow cover, 0.90 for dry pavement surface to 0.94 for wet pavement surface.

- *Palette* iron was selected, which provides finest contrast with color degradation ranging from blue (for lowest temperature) to white (for highest temperature).

- *Noise Reduction* function was activated to reduce clutter.

H) Detection of Water Leak in PVC Pipes

The system designed and developed in this research detected water leaks in PVC pipes successfully as evident from comparison between the detected locations and those found during repair work of these pipes. In the case study shown in Figure 5-11, it was found that the actual leak location was 1.30 m away from the location detected by the developed system. These findings indicate that use of the IR camera overcomes the limitation of the acoustic-based method in detecting water leaks in nonmetallic pipes, and can be used for both PVC and metallic pipes with equal success.

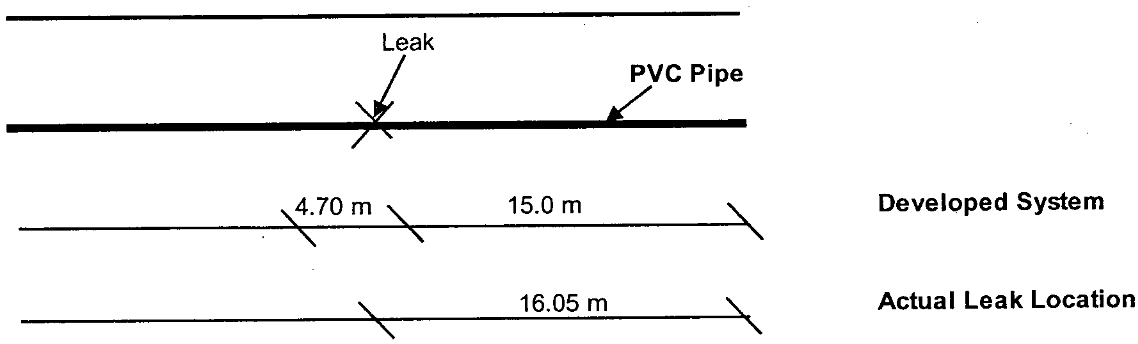


Figure 5-11: Comparison between Leak detected Using Developed System for PVC Pipe and Actual Location of Leak

Step 5: Establishing Approximate Location of Leak

The approximate location of water leak in this research was based on two major steps:

1. Determining areas indicating thermal change at pavement surface (i.e. water leaks)
2. Establishing the relationship between detected leaking area and pipe burial depth

1- Determination of Areas Indicating Water Leaks

Twenty-five pipelines experiencing water leaks were tested using IR camera to develop Equation 5-1. The IR camera used in this research can be set up to provide sequential images (see Appendix C) that automatically numbers the images based on saving period selected by user (e.g. image/2 sec). The user can also adjust the vehicle speed (e.g. 5 km/hr), and can then start scan from origin point such as fire hydrant. Equation 5-1 can be used to locate first thermal contrast detected during pipe scan, which indicating water leaks. The user can then move to that location, and perform further scan to determine the periphery of area indicating thermal contrast (to measure the diameter of virtual base of cone as shown in Figure 5-8).

$$\mathbf{X = \frac{(N\text{-}1) \times 0.28\ S}{R}} \qquad \mathbf{(5\text{-}1)}$$

Where:

X: approximate location of first anomaly indicating water leak from the origin point (m) (i.e. fire hydrant);

N: chronological image number, and N≠1 (i.e. N=1 first image at fire hydrant or the beginning of pipeline);

S: average vehicle speed (km/h); and

R: rate of capturing IR image (image/sec)

2- Establishing the Relationship between Detected Leaking Area and Pipe Burial Depth

Field observations during this research showed that the detected thermal contrast due to water leak on pavement surface approximately resembles the circular base of a cone, with the head representing the location of the leak in the pipe being tested (Figure 5-12).

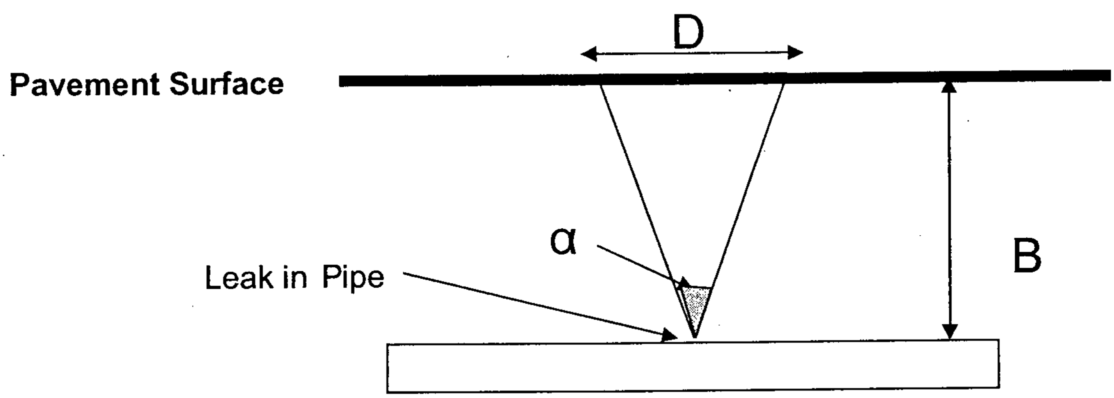


Figure 5-12: Virtual Cone That Indicates Leak Location

Regression analysis was applied to the collected data to establish the relationship between the dependant variable (α), and the independent variables, burial depth of pipe (B), and average diameter (D) of the area indicating thermal contrast at pavement surface due to water leak (See Appendix C). The relationship is shown in Equation (5-2).

$$\alpha^{\circ} = 100.0 - 25.6\ B + 10.5\ D \qquad \textbf{(5-2)}$$

Where:

D: average diameter of area indicating water leak (m); and

B: burial depth of pipe (m)

Based on the *t-test* results (see Appendix C) all t values are greater than $t_{\alpha/2,}$ (2.07) and all p values are less than α (0.05), the hypothesis $H0$ $(\beta i=0)$ can be rejected, and Ha $(\beta i \neq 0)$ holds true. A significant individual relationship is presented in Equation 5-2. Based on Table 5-3, and because the Test Statistic $F= 351 > F\alpha= F_{0.05} = 3.44$ and, p-values $<\alpha=0.05$, which is the targeted level of significance for this study, the hypothesis H0 ($\beta i=0$) can be rejected, and Ha: (one or more of the factors are not equal to zero) is true. A significant overall relationship is presented in Equation 5-2.

According to the above *F*-test and t-test results, the model has both an overall statistical significance and individual statistical significance.

Table 5-3: Analysis of Variances

Source	DF	SS	MS	F	P
Regression	2	2616.2	1308.1	351.22	0.00
Residual Error	22	81.9	3.7		
Total	24	2698.1			

Where:

DF: Degrees of freedom, SS: Sum of squares error, MS: Mean squares error, F: F-value, P: P-value.

Step 6: Validating the Proposed Methodology

The leak locations detected using IR camera for twenty-five water leaks were compared to those detected using the acoustic-based leak finder method. It should be noted that the actual locations of the detected leaks were determined during the repair, which was carried out in the following day (max after 48 hrs) after detection tests. It was found that the actual leak was located within 0.50 m to 1.00 m from the location determined by acoustic-based method .The results are shown in Figures 5-13 and 5-14. As shown in the figures, the detected differences by both methods ranged from 1.01m to 2.95m. These findings indicate the effectiveness of the proposed system, because usually the process of repair requires an open cut with average diameter ranging from 6.00 m to 8.00 m, which was measured during repair.

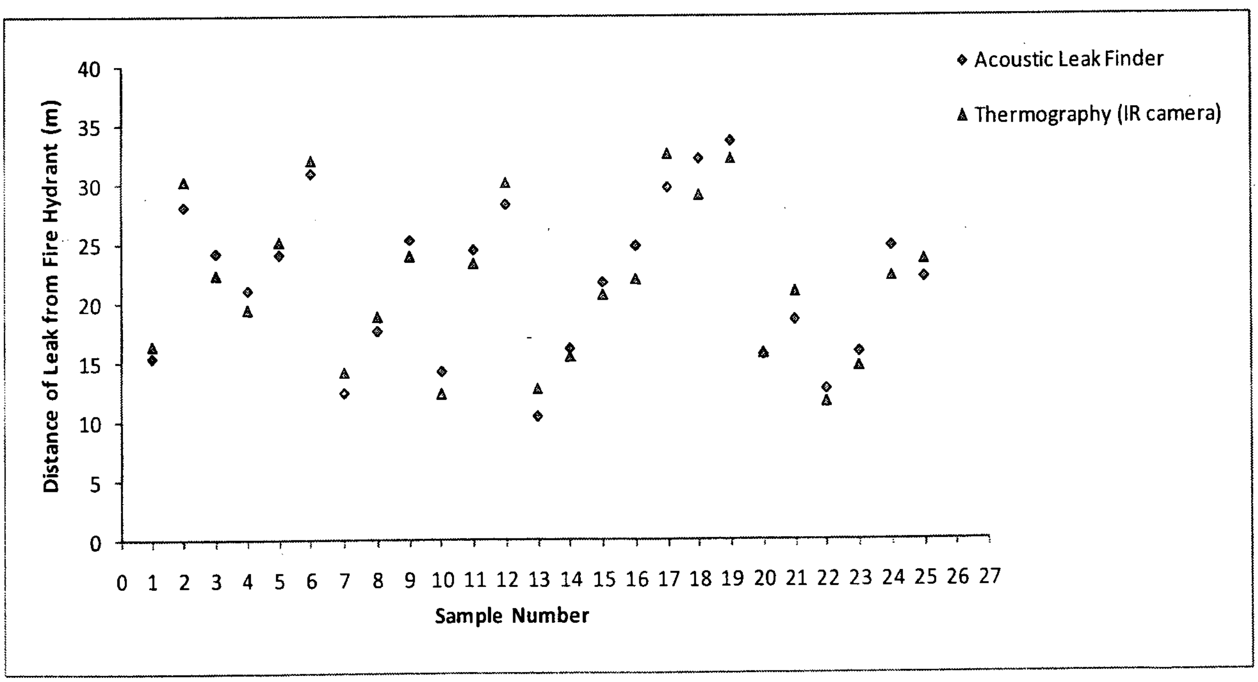


Figure 5-13: Leak Locations (m) using Acoustic Leak Finder Verses IR Camera

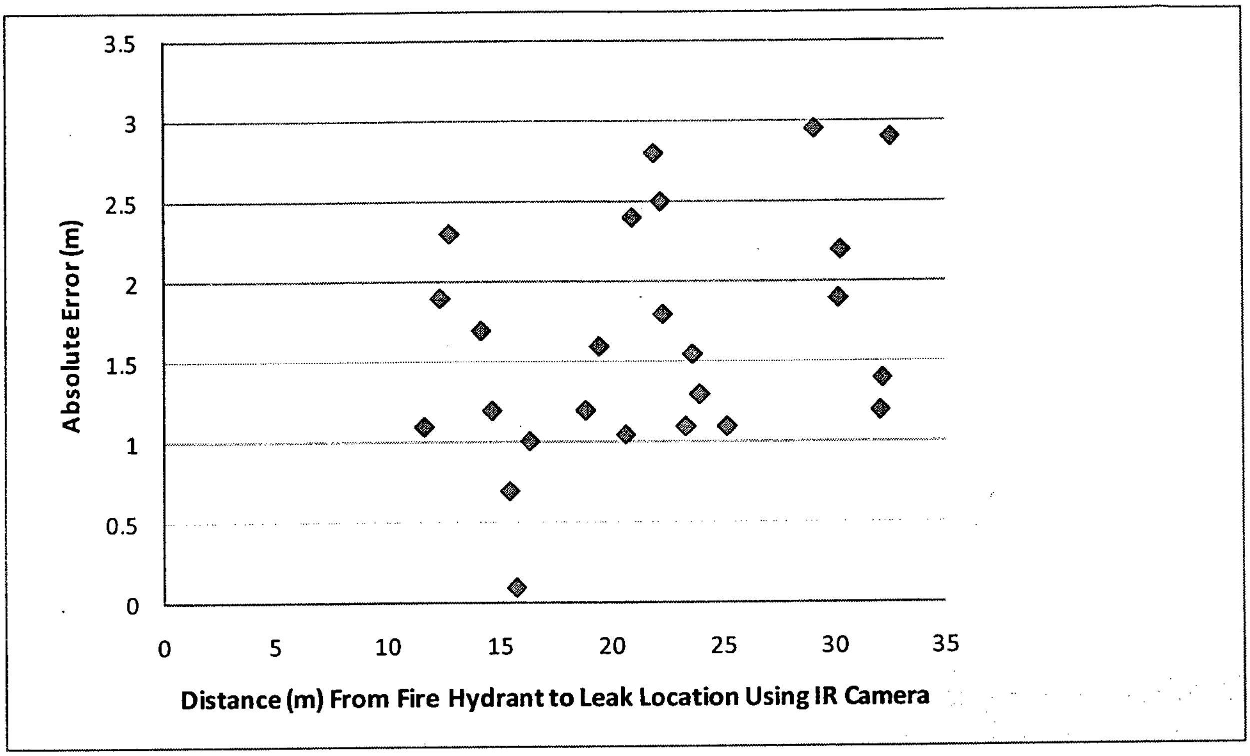


Figure 5-14: Absolute Error (m) Using IR Camera

5.2 Case Study

In this case study, we considered a 150 mm diameter CI water main segment, 48.7 m in length (the distance between two fire hydrants), located 1.80 m below the ground in a residential area of the city. The municipality asks for performing a condition assessment work on that pipeline using thermography method (IR camera) and verifying the results by using the acoustic-based leak finder. The inspection team utilized a vehicle with speed 6 km/hr and the rate of capturing images was set at 0.5 image/sec.

Applying the methodology described above as shown in Figure 5- 15 the user found that

1- Image number 6 showed thermal change (see Appendix C)
2- The user moved to the location representing image number 6 and performed further investigation to determine boundaries of area indicating leak.

Applying Equation 5-1

$$X = \frac{(N\text{-}1) \times 0.28\ S}{R} = \frac{(6\text{-}1) \times 0.28 \times 6}{0.50} = 16.80\ \text{m}$$

The user then moved 16.80 m from the origin (i.e. Fire hydrant #1) to determine the boundaries of leaking area at pavement surface, consequently determined the average diameter, which was 3.04 m as shown in Figure 5-16. The distance from the origin to the place of leak in the pipeline being tested using the developed methodology was 16.42 m, whereas the distance was 15.41m using the acoustic-based method. The results obtained are shown in Figure 5-16.

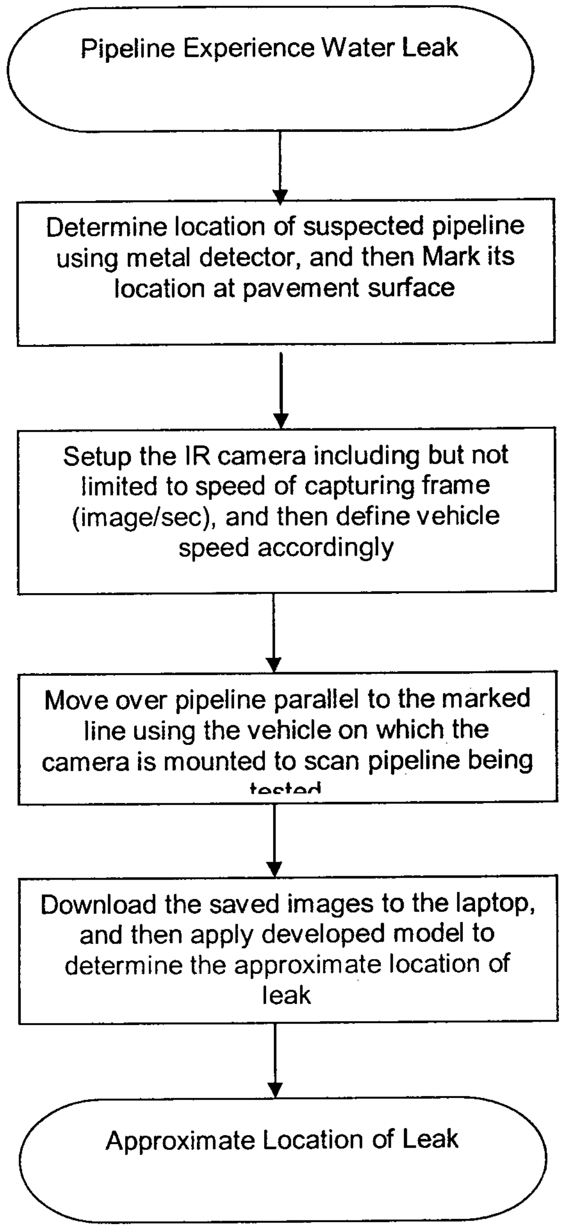


Figure 5-15: Steps of Detecting Water Leak Using the Proposed Methodology

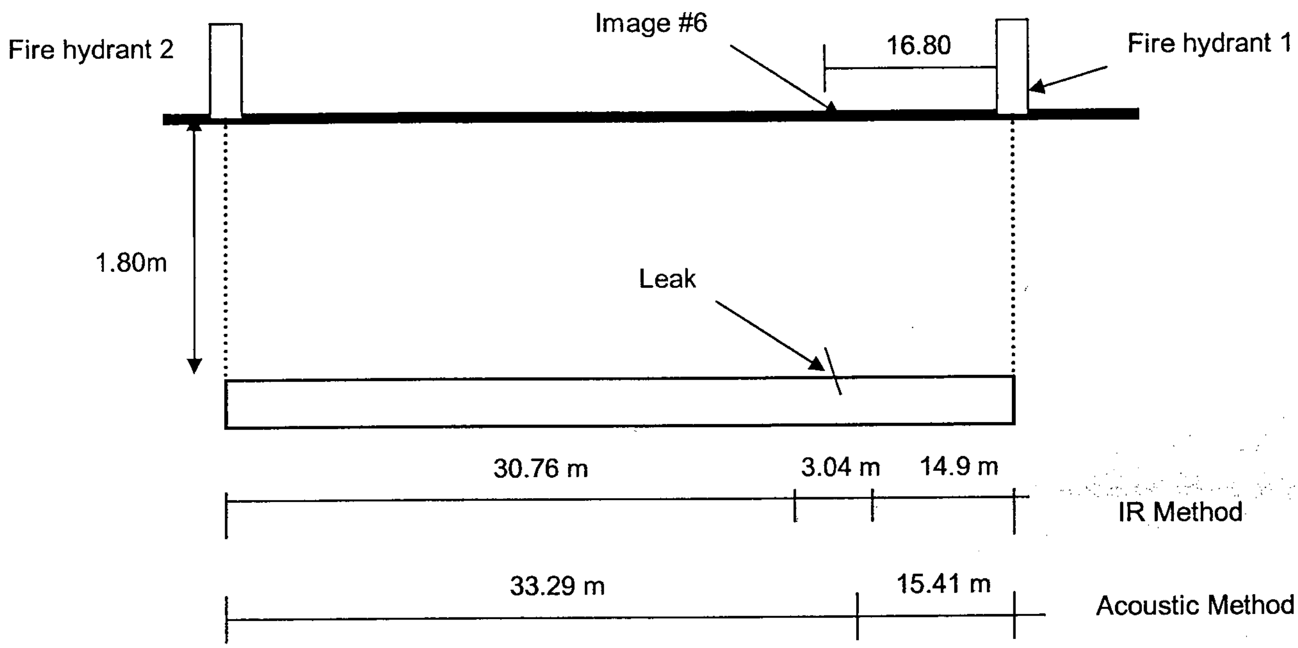


Figure 5-16: Approximate Location of Leak

5.3 SUMMARY AND CONCLUDING REMARKS

This research presents a study on the use of thermography IR camera for detecting and locating leaks of water mains. The study encompassed field investigation, testing as well as modeling development. The fieldwork was conducted on water mains in three locations in the greater Montreal area. The IR camera detected successfully number of leaks as a thermal contrast at pavement surface that occurred during Fall and Spring seasons, while it failed in detecting leaks occurred in Summer and Winter due to high pavement temperature and snow coverage, respectively. Therefore, the model developed in this research is recommended for use in countries with dry moderate weather. The thermal contrast due to water leaks resembles near circular cone base with an angle α that ranging from 80.4° to 123.4°. The head of the cone represents the approximate location of the leak. However, use of the IR camera was not reliable in vicinity of defected sewer pipes due to infiltration into sewer pipes. The near optimum time of using the camera was found to be between 11pm and 8 am during cloudy dry weather in the Fall and Spring seasons, and after 8 am the rising pavement temperature leads to reverse movement of heat towards soil rather than towards the direction of the pavement. The leaks detected using IR camera were compared with those detected using acoustic- based leak finder method and those actually found during repair work. A case study is presented to demonstrate the use and accuracy of the developed methodology.

CHAPTER 6

Forecasting the Remaining Useful Life of Cast Iron Water Mains

6.1 Proposed Methodology

Two types of ANNs are applied: Multi-Layer Perceptron (MLP) and General Regression Neural Network (GRNN). Whereas MLP is the most widely used type of network for forecasting and prediction applications (Maier et al. 2000), GRNN is a promising technique for building predictive models (Thwin and Quah 2003). Multiple-regression is used as a benchmark to compare the performance of ANNs. Each of the three techniques mentioned above was used to develop a model that predicts remaining useful life of cast iron water mains. The methodology calls for testing each model for significance and accurate representation of collected data, and then retain the model that performs the best (see Figure 6-1).

The output values (i.e. remaining useful life) utilized in model development ranged from zero to 200 years, while, the input variables utilized in model development were selected from intensive study, experts' interviews, and field investigations. Sample of the data collected is shown in Appendix D. These factors were clustered under four groups: physical, mechanical, operational, and external environment, as summarized in Table 6-1 along with their minimum and maximum values. A brief description of the four groups follows in the next section

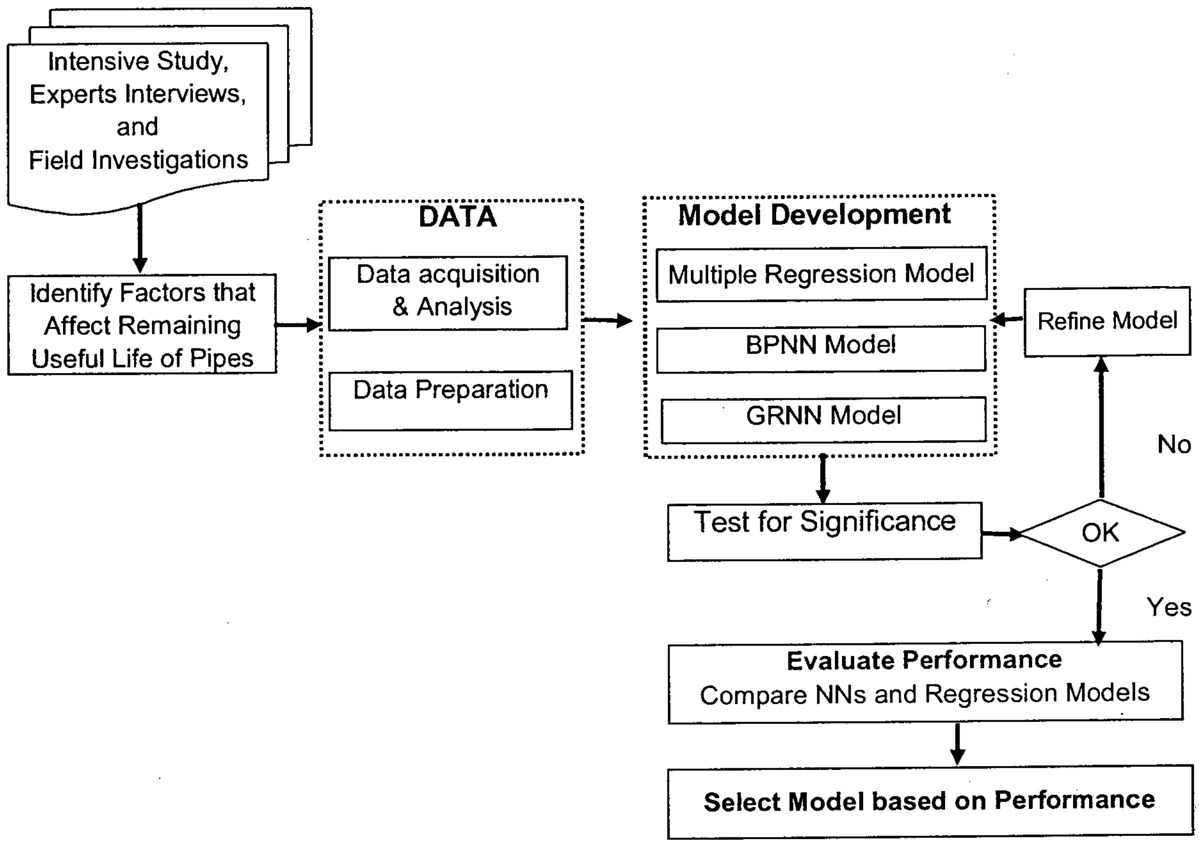


Figure 6-1: Methodology of Model Development

Table 6-1: Input Factors and Their Values

Input	Value
Physical Factors:	
-Pipe age	1-150 years
-Pipe diameter	150-200mm
-Manufacturing	(Pit/Spun) Cast Iron
-Pipe wall thickness	6-14mm
-Corrosion depth	1-5mm
Mechanical Properties:	
-Bursting tensile strength	76-305 MPa
-Modulus of rupture	207-445 MPa
Operational factors:	
- Internal pressure	1000-1724 KPa
-Surge pressure	600-827KPa
-Safety factor	1-2.5
Ext. Environment Factors:	
-soil pH	5-8.7
-soil aeration index	4.32-9
-soil resistivity	680-11000 ohm-cm
-Buried depth of pipe	1.3-2.4m
-External Loads	18-45 KN/m

6.2 Factors Affecting Remaining Useful Life of Water Mains

Physical Properties

The physical properties considered in this research include pipe age, pipe diameter, pipe wall thickness, corrosion depth, and pipe manufacturing. Pipe age is an important factor indicating the maximum period the pipe will withstand the effect of surrounded environment, operational condition, and external loads (O'Day 1983; Sacluti et al. 1998; Rajani et al. 2000; Rajani and Makar 2001; Infraguide 2003; Sinske and Zietsman 2004). Recent studies revealed that pipes with smaller diameter pipes are more vulnerable to fail than pipes with larger diameter (Pelletier et al. 2003; Infraguide 2003). Other studies revealed that corrosion penetrates thinner walled pipes more quickly than thicker walled pipes.

It was also reported that an increase in the corrosion depth with time, particularly in corrosive soils, increases the likelihood of failure. The effect of pipe manufacturing method (Pit/Spun) was also considered based on previous studies (Romanoff 1964; Rossum 1969; Gummow 1984; O' Day et al. 1986; Dorn 1996; Rajani et al. 2000).

Mechanical Properties

The design of CI water mains, as described in design standards C101-67 (AWWA 1977), relies on two measures of strength, namely, ***"bursting tensile strength"*** and ***"rupture modulus".*** These two properties were considered as input variables of the developed models. The first property involves destruction of a full length pipe by internal pressure, while the second property is used as a measure of bending strength of the pipe material. Several researchers have studied the relationship between the mechanical properties and degradation of pipes (Kirby 1977; Yamamoto et al. 1983; Conlin and Baker 1991; Rajani et al 2000). Their studies revealed that degradation of a pipe tensile strength due to its corrosion is a good indication of the pipe deterioration.

Operational Conditions

Operational conditions involve internal water pressure, which greatly influencing remaining life of the pipe (Infraguide 2003). The design procedure for grey cast iron mains as outlined in C101-67 (AWWA 1977) considers a safety factor of 2.5 (2.5 times the external and internal working loads) to determine the minimum wall thickness for a pipe of specific diameter. This safety factor decreases with time due to aging factors and load variations (e.g. increase of traffic loads). In common practice, a safety factor of 1.2 is considered a threshold value for repair action (Rajani et al. 2000; Rajani and Makar 200).

External Environment Factors

There have been several studies analyzing the influence of soil properties on the corrosion of cast iron (Romanoff 1964; Rossum 1969; Gummow 1984; Dorn et al. 1996; Rajani et al. 2000). These studies revealed that changes in surrounding soil properties such as soil pH, soil aeration, soil resistivity, depth of burial and external loads have considerable influence on the corrosion rate. Acidic soil (low pH, <6) promotes direct chemical action on the pipe wall, which in turn promotes corrosion, unlike basic soil (high pH, >8). Poorly aerated soil presents a favorable environment for the growth of anaerobic microorganisms (organisms growing without oxygen) which can lead to very rapid corrosion. Soil resistivity influences the current in the corrosion cells. For instance, soil with low resistivity (e.g. < 1000 ohm-cm) is more aggressive than soil with a higher resistivity (e.g. > 5000 ohm-cm). Rajani et al. (1996) found that pipe burial depth is an important factor in cases where frost conditions exist. In addition, external loads arising from traffic also affect the life of pipes in cases of poor bedding conditions (Infraguide 2003).

6.3 Data Acquisition and Analysis

The data used for development and validation of models were collected from 16 municipalities in Canada and in the US. Canadian municipalities include the cities of Edmonton, Winnipeg, Toronto, Vancouver, Moncton, Montreal, Ottawa Carlton and Quebec City. The US municipalities include the cities of Boston, San Francisco, Philadelphia, Minneapolis, Chicago, Denver, St. Louis and Washington (sample shown in Appendix D). The collected data were split randomly into two groups; one to develop the model (80%= 544 patterns) and the other to verify it (20%= 136 patterns). Fifteen input factors described earlier (Table 6-1) were initially considered for the development of models presented in this research. The actual remaining useful life was estimated by predicting the time when the thickness of the pipe wall being sampled will reach the minimum permissible limit stated in AWWA standards (1977) due to corrosion and other external environment factors, and when the safety factor of the pipe will fall below a minimum acceptable value set by the utility owner. The steps for determining approximate actual remaining useful life are shown in Figure 6-2.

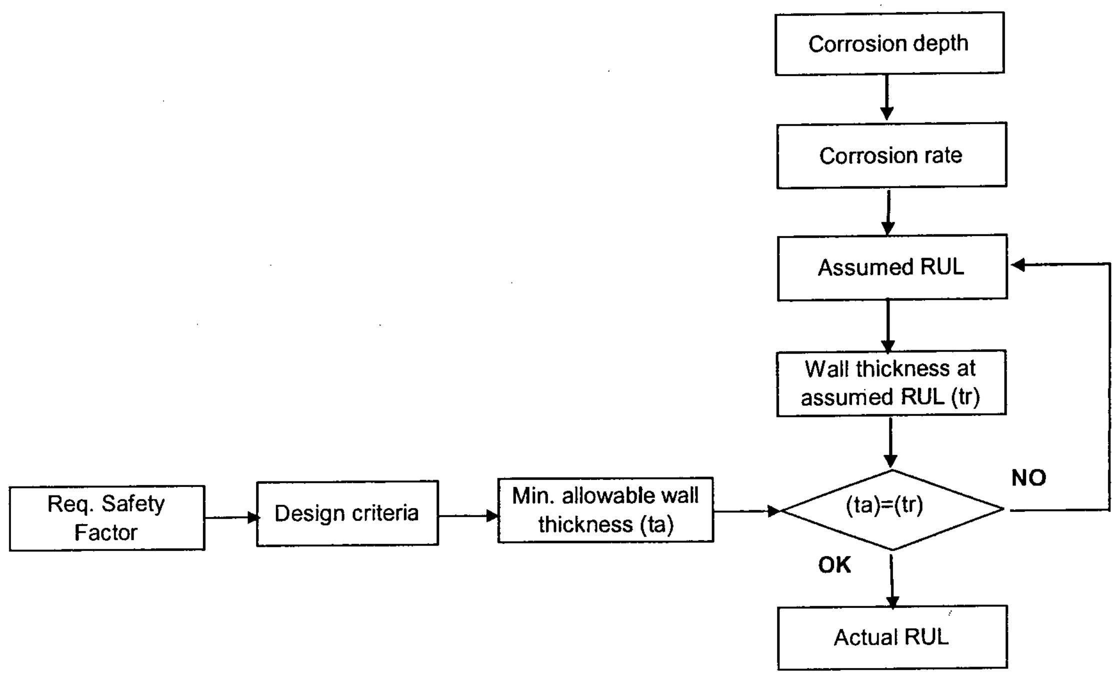


Figure 6-2: Flow Chart for Preparation of Output Values (RUL)

The corrosion rate was calculated using Rossum's equation (1996) based on principles of electrochemistry Equations 6-1 and 6-2). The hypothesis for this equation considers corrosion as a consequence of cell potential occuring over the pH range of 5 to 9.

The model that was developed by Rossum for corrosion growth rate is as following:

$$\mathbf{p=K_n\,Z^n} \qquad \textbf{(6-1)}$$

$$\mathbf{Z= [(10\text{-}pH)\ Time/\rho_{soil}]} \qquad \textbf{(6-2)}$$

Where

p: corrosion depth (mm);

Time: is time of exposure of the pipe to the particular soil (yr);

ρ_{soil}: soil resistivity (Ω-cm);

n: soil aeration constant; and

Kn: proportionality constant (mm/yr, Ω-cm)

Box-Cox power transformation was applied to the input factors to improve model's fit (Minitab 2006). Box-Cox transformation estimates lambda (λ) values, which minimize the standard deviation of a standardized transformed variable. The resulting transformation is $\mathbf{Y}^{\lambda}$ when $\lambda \neq \mathbf{0}$, unless $\lambda = 0$, in which case the natural log (Ln) is considered (if $\lambda = 2$ then $\mathbf{Y}^{\lambda} = \mathbf{Y}^{2}$). Sample of Box-Cox transformation applied to the input parameter pH is shown in Figure 3-6. More details can be found in Myers (2000).

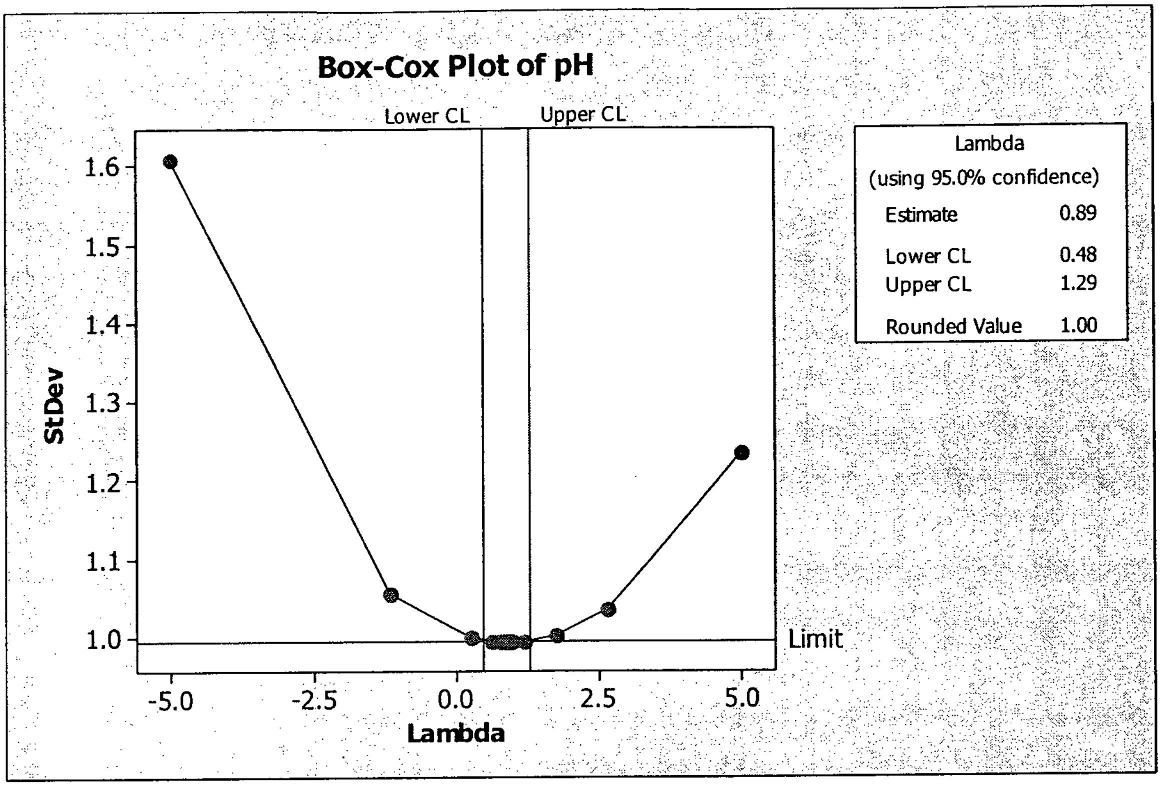


Figure 6-3: Sample of Box-Cox Transformation for the Input Parameter (pH)

6.4 Model Design and Development

6.4.1 Multiple-Regression Model

An effort was made to identify the significant factors for later use in the model for which sixty trials were carried out. The study resulted in using only eight factors out of initial fifteen factors. These selected eight factors are corrosion depth, $(\text{Age})^{0.5}$, bursting tensile strength, soil pH, $(\text{soil resistivity})^{0.23}$, $(\text{soil aeration index})^{-1}$, Ln (external loads), and the safety factor. These eight factors are referred later to best subset. Ideally, one should select the smallest subset that fulfills certain statistical criteria (Minitab 2006). The importance of using only significant input variables is to reduce the degree of noise in the data introduced into the model to obtain ,ore accurate output. The best subset regression is carried out using Minitab software and the best subset was selected as one with highest R^2 value, and relatively small Mallows C_P value. Mallows' C_P value is used to compare the full model to a model with a subset of predictors. Generally, one should search for a model that has small Mallows' C_p value, which is also close to p value as defined below.

$$\boldsymbol{C_p = SS_{res}/MS_{res} - N + 2p} \tag{6-3}$$

Where:

SS_{res}: the residual sum of squares for the model with p-1 variables,

MS_{res}: the residual mean square when using all available variables,

N: the number of observations, and

p: the number of variables used for the model plus one.

A small C_p value indicates that the model is relatively precise (has small variance) in estimating the regression coefficients and in predicting future responses. Models with considerable lack-of-fit and bias have values of C_p larger than p. More information can be found in Montgomery and Peck (1982). The selected subset in this study has R^2 of 85.6% and Mallows C_P value of 8.1.

Regression analysis was performed using a 95% confidence level to calculate the regression coefficients. The regression coefficients were determined using 544 patterns (80% from data set), and used to construct Equation (6-4)

$$\text{RUL} = [6.75 + 1.03\,C - 0.28(A)^{0.5} + 0.01(S) + 0.22\,pH - 18\,(\rho)^{-0.23} - (3.5 / K) - 0.2\,\text{Log}_e\,W - (0.281 / SF)]^{3.57} \tag{6-4}$$

Where:

RUL: Remaining Useful Life of CI water main (yr); ***C***: corrosion depth (mm); ***A***: Pipe age (yr); ***S***: Bursting tensile strength of pipe (MPa); ***pH***: Soil alkalinity/acidity; ***ρ***: Soil resistivity (ohm-cm); ***K***: Aeration Index; ***W***: External Load (KN/m); and ***SF***: Load safety factor.

Based on *t*-test results all *t* values greater than $t_{\alpha/2}$ (2.26) and all *p* values lesser than α (0.05), the hypothesis H0 ($\beta i=0$) can be rejected, and Ha ($\beta i \neq 0$) is true. A significant individual relationship is present for the Model in Equation 6-4. Based on Table 6-2, because the Test Statistic $F= 425.5 > F\alpha= F_{0.05} = 1.8799$ and, p-values $<\alpha=0.05$, which is the targeted level of significance for this study, the hypothesis H0 ($\beta i=0$) can be rejected, and Ha: (one or more of the factors are not equal to zero) is true. A significant overall relationship is presented for the model in Equation 6-4. According to the above *F*-test and *t*-test results (see Appendix D), the remaining useful life model has both an overall statistical significance and individual statistical significance. Hence, the model can go through the validation process.

Table 6-2: Analysis of Variance

Source	DF	SS	MS	F	P
Regression	8	681	85.1	425.5	0.000
Residual Error	540	114	0.2		
Total	548	795			

Where:

DF: Degrees of freedom, SS: Sum of squares error, MS: Mean squares error, F: F-value, P: P-value

6.4.2 Back Propagation Neural Network Model

The MLBP model has three layers, input, hidden, and output layers as shown in Figure 6-4. The number of neurons in the input layer equal the number of input variables stated earlier in multiple–regression section. The output layer of the proposed network consists of one neuron, which represents the remaining useful life of CI water mains. The commercially available neural network software package NeuroShell 2, which uses the back-propagation algorithm in training was used for development of the model. Based on number of trials, the input layer transfer function was selected to be linear [0, 1], while the Gaussian and Hyperbolic Tangent tanh functions were selected for the hidden layer and output layer, respectively. The number of hidden layers in the trial study ranged from 1 to 3, and the number of hidden neurons ranged from 21 to 27. This range was selected using the following equation (NeuroShell-2 1996):

$$N = 0.5(X + Y) + (Z)^{0.5} \qquad \textbf{(6-5)}$$

Where: N = number of neurons in the hidden layer; X = number of input neurons; Y = number of output neurons; and Z =number of patterns in the training set. One hidden layer was selected with 24 hidden neurons based on the trial study. Cross-validation was used to determine when training should be stopped to prevent over fitting. Learning and momentum rates ranged from 0.05 to 0.3.

Based on these trials the learning rate was set at 0.058, and a value of 0.268 was assigned to the momentum.

The prepared data (680 patterns) were used in developing the NNs. The data were randomly divided into 408 patterns (60%) for the training set, 136 patterns (20%) for the testing set and 136 patterns (20%) for the validation set. The validation set was not exposed to the network during training or testing processes (patterns not seen by the network before), and was used to test the generalization capability of the developed network.

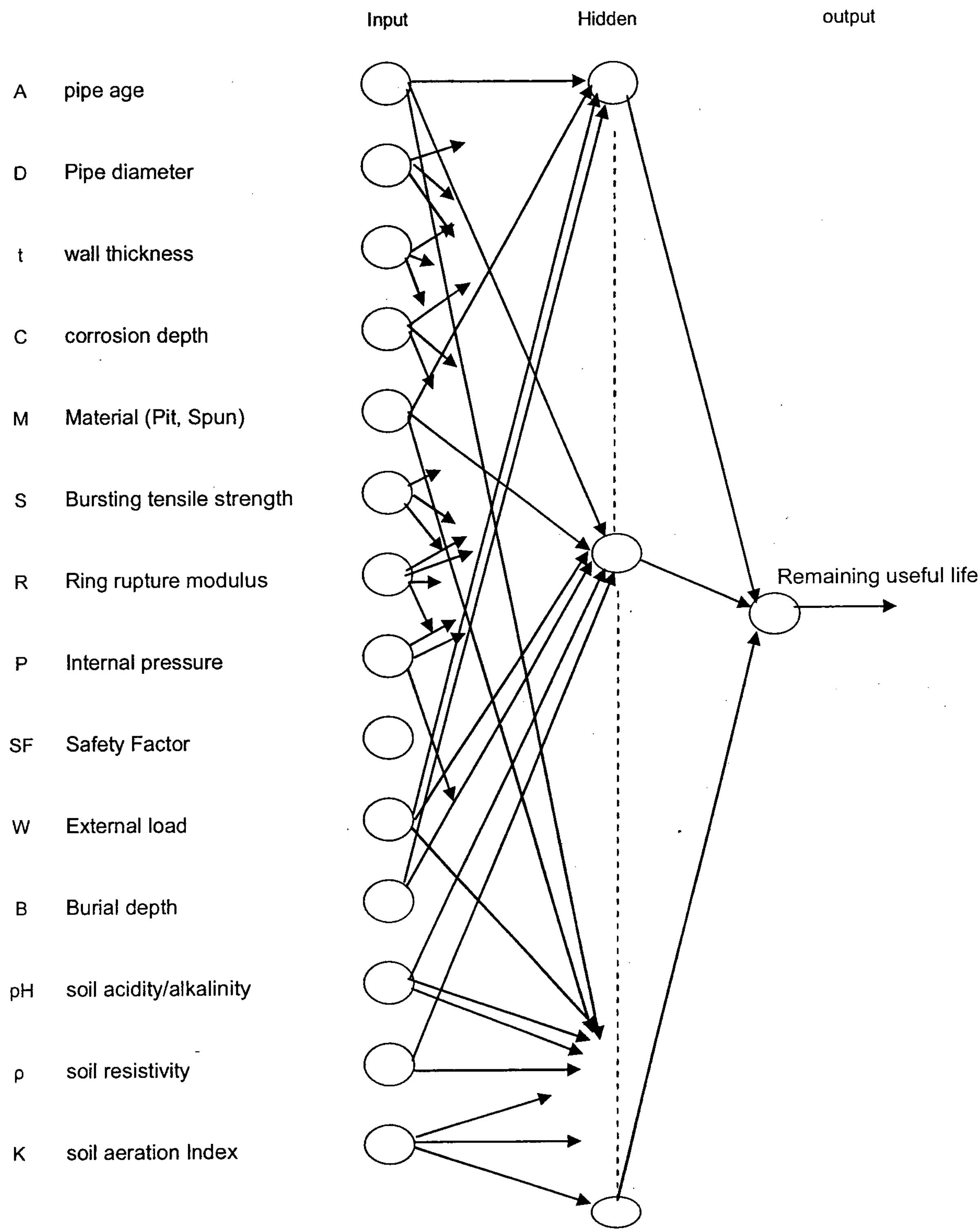


Figure 6-4: Input/ Output Diagram for the Neural Network

6.4.3 General Regression Neural Network Model

GRNN is a three-layer network, in which the number of hidden neuron is equal to the number of input patterns. There are no training factors such as learning rate and momentum as in the back-propagation, but there was a smoothing factor applied after the network was trained. GRNNs are known for their ability to train quickly on sparse data sets, and their applications are able to produce continuous valued outputs. GRNN is a type of supervised network. It is especially useful for continuous function approximation (Ward Systems Group, 1996; Mie and Tong 2005; Gibbs et al. 2006; Irwan et al. 2007). For the GRNN models, the training and testing data sets were combined into one data set. GRNN networks work by comparing patterns based upon their distance from each other, which can be computed using the City Block and the Euclidean Distance method. The first method was found to be computationally quicker but produced slightly less accurate predictions when compared to the second method. Hence, due to the limited data and relatively fast run time, the Euclidean Distance method was used for all GRNN models. Genetic Algorithms (GA) were used to calibrate the multiple smoothing factor of the GRNN. Termination criterion of 20 generations with no improvement of at least 1% was used.

6.5 Analysis of Results

A sensitivity analysis was carried out to study the effect of the input attributes on the overall performance of the developed BPNN model. The general performance of the model was measured by the values of the coefficient of multiple determination (R^2) and residual errors (NeuroShell-2 1996) using 20% of the data set (136 patterns). In this analysis, several trials were conducted with different combinations of input variables and their respective performances were compared. Based on the analysis of the results obtained, the tested eight attributes in the input layer of the developed network indicated a success rate of 90%. As shown in Figure 6-5 the study revealed that corrosion depth, pipe age and soil resistivity have significant contributions to the remaining useful life. The other seven input variables were excluded due to their insignificant contribution to the model.

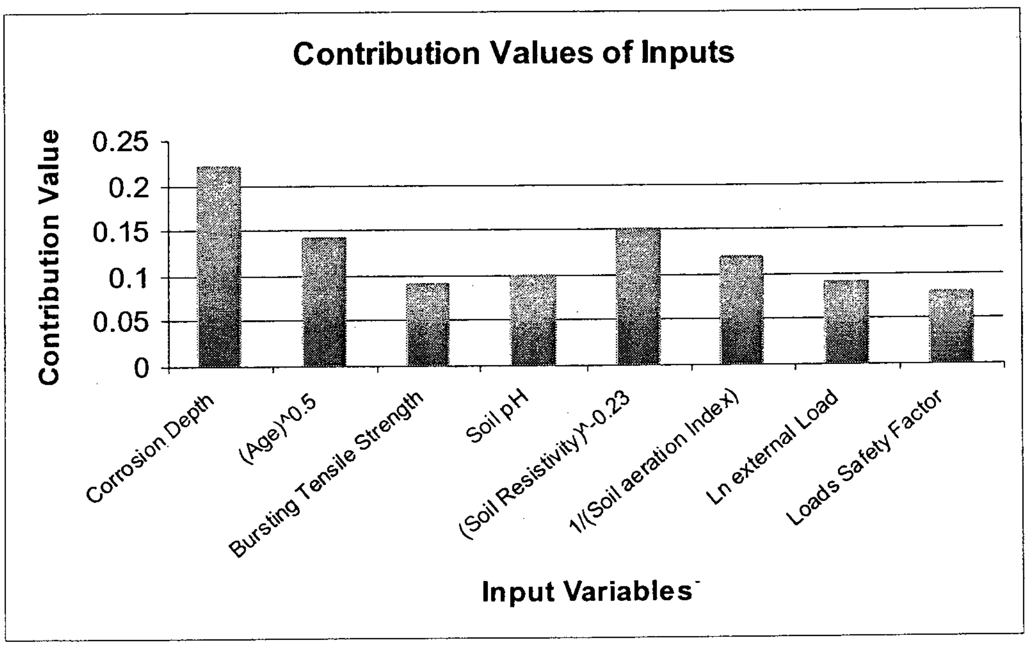


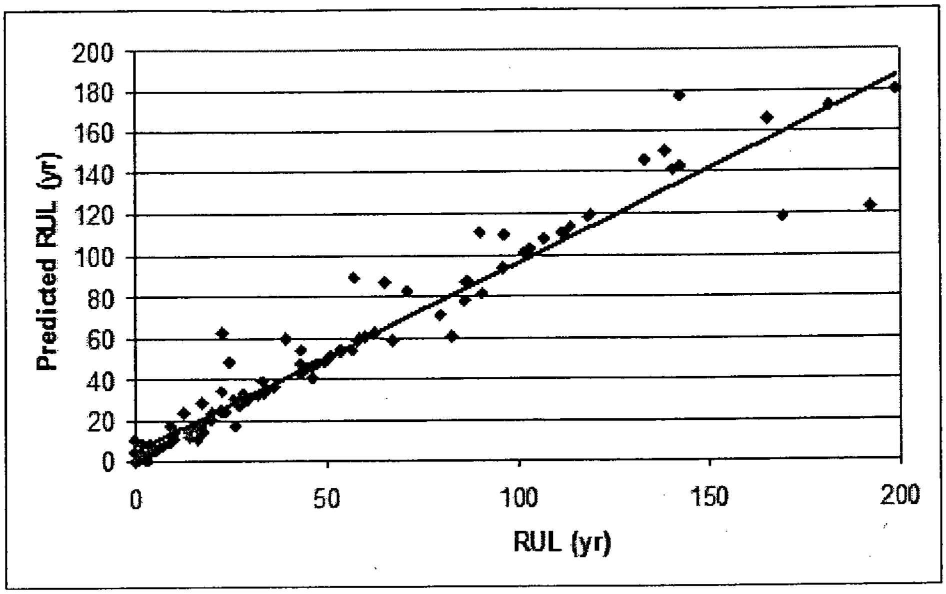
Figure 6-5: Contribution of the Input Variables Considered

The design and the generalization results obtained from the MLPNN and GRNN are summarized in Table 6-3. As shown in Table 6-3 and Figures 6-6, and 6-7 the two developed NN models have relatively high coefficients of multiple determination indicating model reliability (Fahmy and Moselhi 2009).

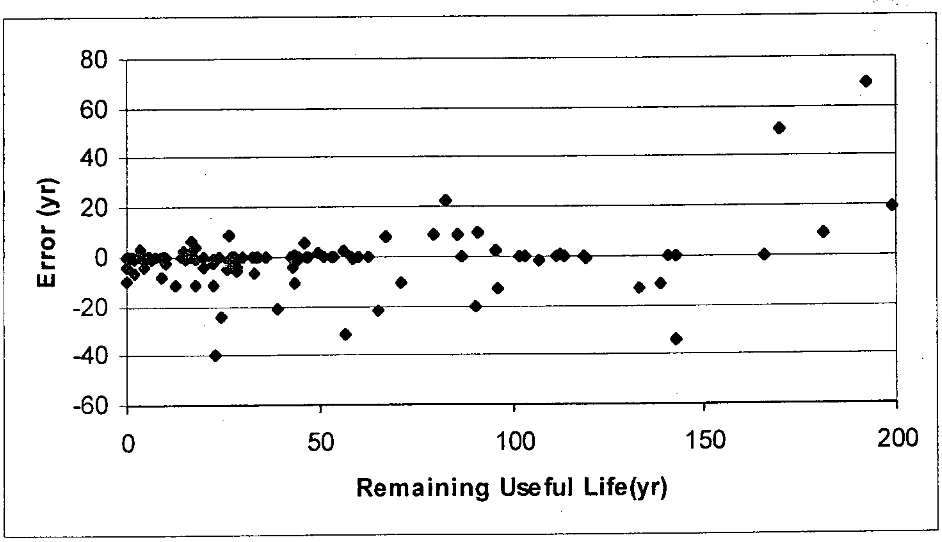
Table 6-3: Comparison between Final MLPNN and GRNN

	MLBPNN model	**GRNN model**
Patterns	408 training pattern (60% from data set) 136 for testing, and 136 for validation	
Input layer	8 inputs	8 inputs
Hidden layer	One hidden layer with 24 nodes	One hidden layer with 408 nodes
Output Layer	Remaining Useful Life(yr)	
Algorithm used for minimizing error	Steepest decent	Genetic Algorithms
Activation function(s)	Gaussian (hidden) and Hyperbolic Tangent (tanh)(output)	Gaussian
R^2 for test set	0.96	0.95
R^2 for generalization set (validation)	0.907	0.89
Mean absolute error	0.12	0.174
Max. absolute error	0.626	2.035
Min. absolute error	0.003	0.003

Note: The collected data used in model development were acquired from16 municipalities in Canada and the US, and was split randomly into 60% for training, 20% for testing, and 20% for generalization.



(a)

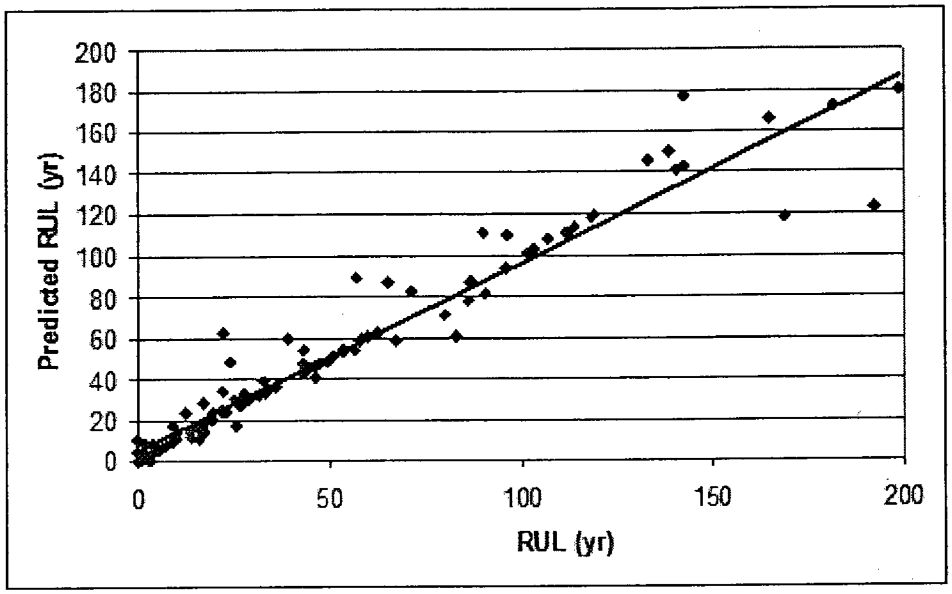


(b)

Figure 6-6: MLBPNN Model Prediction Versus Observed Sample

(a) RUL Verses Predicted RUL (b) Error (yr)

(a)



(b)

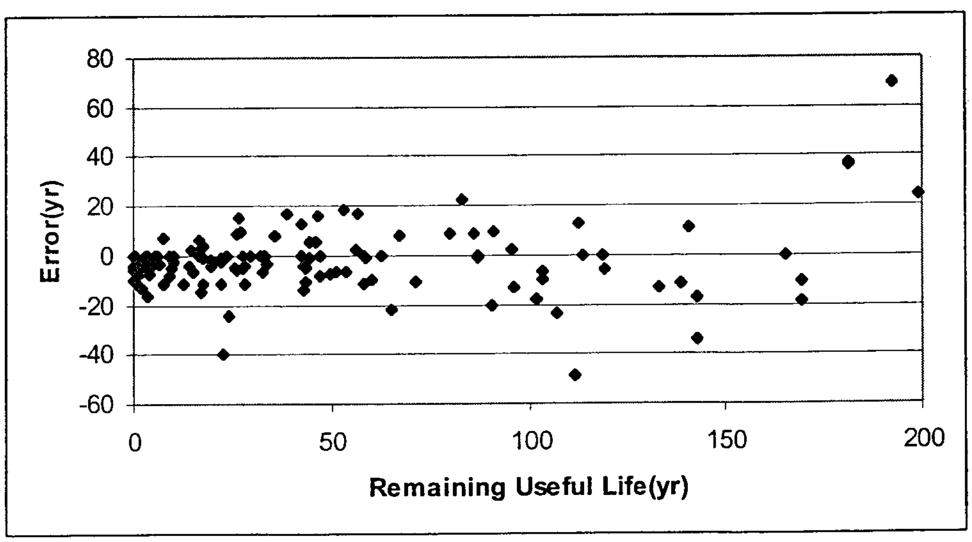


Figure 6-7: GRNN Model Prediction Versus Observed Sample

(a) Actual RUL Verses Predicted RUL (b) Error (yr)

Table 6-4 shows a comparison of the estimated remaining useful life of different pipe samples using Rossum (1969), Rajani et al. (2000), and the designed and developed models in this research. The analysis shows that the developed model, apparently, predicts shorter residual lives than that of Rajani et al. model. This could be due to the consideration of external environment factors used as input variables. These factors act on the external surface of buried pipes and lead to accelerate corrosion rates.

Table 6-4: Comparison between Existing Models and Developed Models

		Developed Models		
Rossum	Rajani et al.	(GRNN)	(BPNN)	M.Regression
15.0	18.0	18.2	14.1	8.4
81.3	100.0	80.8	93.5	37.7
10.5	12.0	12.5	10.6	8.8
65.9	90.0	62.9	87.0	42.4
10.9	15.0	14.3	13.8	12.7
72.8	95.0	69.8	79.3	66.7
18.6	25.0	25.1	14.2	15.2
136.5	150.0	130.1	135.2	114.6
36.8	50.0	40.2	37.8	28.4
18.0	25.0	16.5	16.1	14.2
37.6	50.0	40.6	32.7	34.3
47.3	70.0	51.5	50.3	39.3

The estimated remaining useful life predicted by the model developed in this research is used for condition rating of the pipeline(s) being considered as described by Moselhi and Fahmy (2007), and shown in Figure 6-8.

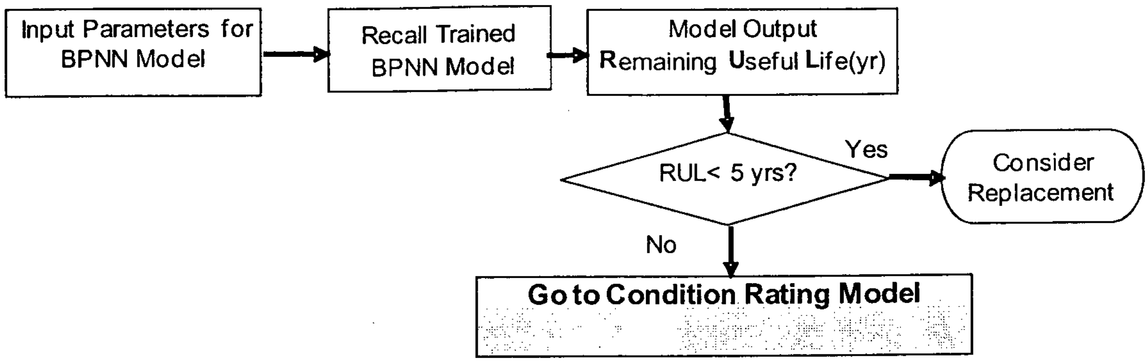


Figure 6-8: Model Input/ Output Diagram

6.6 SUMMARY AND CONCLUDING REMARKS

The study presented in this paper revealed that data-driven modeling methods are effective in forecasting remaining useful life of cast iron water mains. Two types of ANNs were applied; the Multi-Layer Perceptron (MLP) and the General Regression Neural Network (GRNN). Multiple-regression was also used as a benchmark to compare the performance of the ANNs. Fifteen deterioration factors were initially considered in designing the developed models. Using significant input factors reduces the degree of noise in the data introduced into the model, and consequently; accurate results are obtained. The study revealed that the developed BPNN best fit the collected data, and therefore it was used in condition rating of pipe(s) being considered as described in chapter eight and in Moselhi and Fahmy (2007). The model found application to both single pipe and group of pipes. In addition, the use of factors such as soil resistivity and soil pH as input variables facilitates the use of the model at different locations around the globe.

CHAPTER 7

Prediction of Failure Rates of Cast Iron Water Mains

7.1 Model Design and Development

Model development considers the design and development of three predictive models for failure rates of cast iron water mains; two of these models are NNs and the third is multiple-regression model. The three models described here represent the phenomena being modeled and the model showing the best performance was selected. The steps of model development in detail are outlined in Figure 7-1.

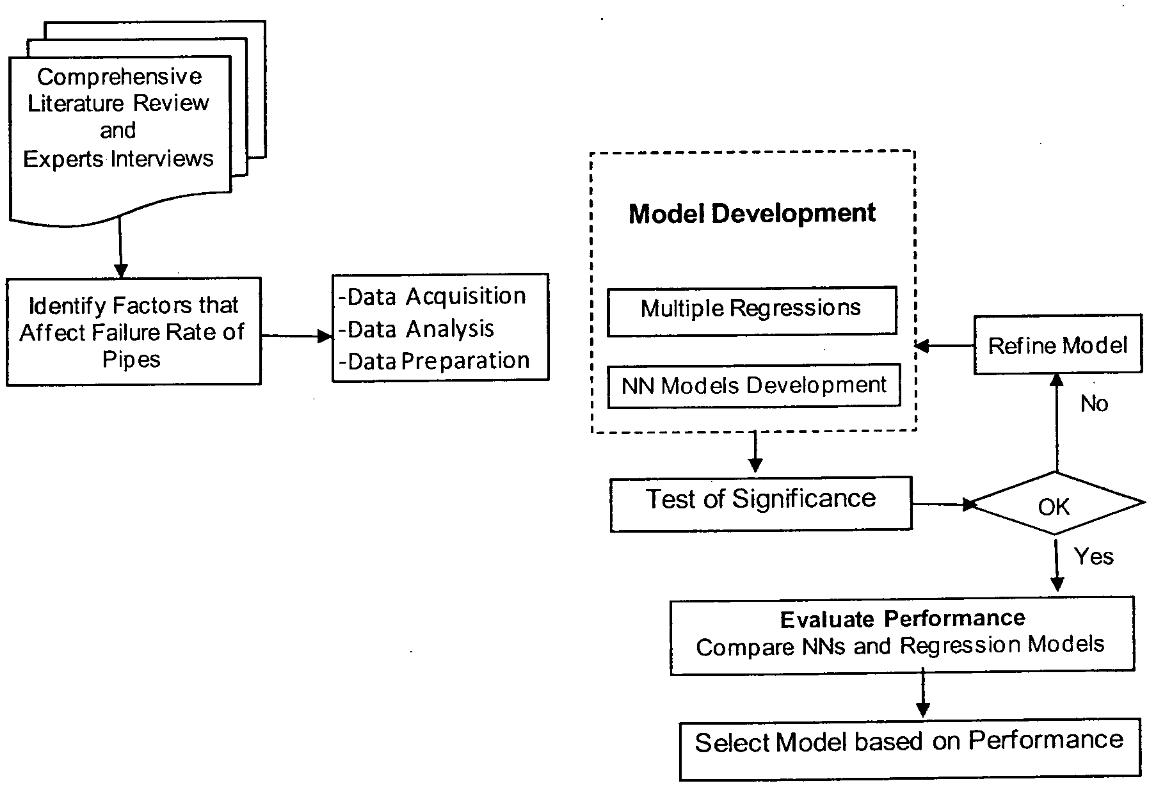


Figure 7-1: Methodology of Model Development

7.2 Identifying Factors That Affect Failure Rate

The following eight main factors were identified based on a comprehensive literature review, interviews with experts, and field observations.

Pipe Age: represents the operating conditions including aggressiveness of surrounding soil and has been regarded as a main factor that affects the failure rate by several researchers (O'Day 1983; O'Day et al 1986; Sacluti et al. 1998; Rajani and Makar 2000; Infraguide 2003; Sinske and Zietsman 2004; Yong 2006).

Pipe Manufacturing: the effect of pipe manufacturing method (Pit/Spun) was considered based on previous studies (Romanoff 1964; Rossum 1969; Gummow 1984; O' Day et al. 1986; Dorn 1996; Rajani et al. 2000).

Pipe Length: A longer pipe generally experiences more failures due to greater exposure to diverse conditions like poor surrounding fill, ground movement due to traffic loading and underground water tables, besides increased exposed area due to length (Loganathan et al. 2000; Skipworth et al. 2002; Infraguide 2003, Moselhi and Fahmy 2008).

Pipe Diameter: Pelletier et al (2003) found that failure rates in small-diameter pipes are greater than those in large-diameter pipes. Similar finding was also reported in a study presented in Infraguide (2003).

Depth of Cover: Rajani et al. (1996) found that pipe burial depth is an important parameter in cases where frost conditions exist.

External Loads: External loads affect the pipe failure and it was found that heavy traffic load would increase the possibility of pipe failure, especially when poor bedding exists (Infraguide 2003).

Average Ambient Temperature: In the present study, the analysis of the collected data revealed that most of that failures occurred during winter season. This finding is also in agreement with findings of other studies (Walski and Pelliccia 1982, Rajani et al. 1996, Sacluti et al 1999, Rajani et al 2000 and Kleiner and Rajani 2001), where temperature was found to affect the failure rate of cast iron water mains.

Average Precipitation: Baracos et al. (1955) who observed that water mains failures in Winnipeg largely occurred between September and January and peaked especially when dry soil conditions existed after a hot summer or just prior to spring thaw. The analysis of the data collected in the present study also confirmed this observation. The influence of soil moisture on water main failure rates was also observed by others (Newport 1981 in the UK, and Hudak et al. 1998 in the US.).

7.3 Data Acquisition and Analysis

Data were collected in both electronic format (GIS, Microsoft Excel, and Acrobat PDF) and in form of hard copies. The study showed that the grey cast iron pipe group is the largest group, with a total length of nearly 130 km, and the majority of the networks have pipe sizes ranging from 150 mm to 200 mm (85%). Less than 10% of the network have pipe sizes of more than 350mm as shown in Table

7-1. The study also showed that about 80% of pipe failures in Quebec are of circumferential type.

Table 7-1: Distribution of Cast Iron Pipes by Diameter and Associated Length

Pipe Diameter (mm)	Pipe Length (Km)
100	2.27
150	73.43
200	35.64
250	4.86
300	4.5
350-400	5.01
500+	4.31

The collected data included information like pipe ID, pipe location, pipe material, pipe size, date of installation, date of breaks, number of breaks per km per year of water mains, classification of breaks (see sample of filtered collected data in Appendix E)

7.4 Data Preparation

Data were split randomly into two groups; one for model development (80%) and the other for verification of the developed models (20%). The data collected from GIS files and hard copies were passed through a filtering process to prepare the input-output patterns needed for the development of the NNs models. This process included associating the failures records to individual pipes, grouping pipes by material, diameter and age as well as identifying and removing inconsistent data. It should be noted that the Box-Cox power transformation (Minitab 2006) is applied to the input variables to improve model's fit.The transformation takes the original data to the power λ, unless $\lambda = 0$, in which case the natural log (Ln) is considered. The developed model presented in this research considered initially eight input variables, which are pipe size (mm), pie age (yr), pipe manufacturing (Pit/Spun), pipe length (m), burial depth (m), external Load (Kn/m), ambient temperature (^{0}C), and average precipitation (mm). An effort was made to identify the significant factors for later use in model (See Appendix E). Forty trials were carried out and only five main factors out of initial eight factors. These factors are pipe length, pipe age, pipe depth, average ambient temperature and average precipitation, were used in the study. Four input parameters were generated by applying the Box-Cox power transformation to the independent variables in order to improve model's representation of the collected data. These four inputs are $(\text{age})^2$, $(\text{temperature})^2$, Ln (Length), and Ln (depth).Table 7-2 depicts the independent input and output parameters and their respective minimum and maximum values used in model development and its validation.

Table 7-2: Independent Input and Output Parameters

Input	Value
Physical Factors:	
-Pipe age	1-150 years
-Pipe Manufacturing	Pit/Spun
-Pipe diameter	150-200mm
-Length of pipe	2-112m
Ext. Environment Factors:	
-Average temperature	(-17) ^{0}C-18 ^{0}C
-Average precipitation	9-171 mm
-Buried depth of pipe	1.3 m-2.4 m
-External Load	30-45 KN/m
Output	**Value**
Annual Failure Rate	0.23-31.50 failure/Km/Yr

7.5 Applying Data on Existing Models

The data acquired are applied to Shamir and Howard (1979) and Walski and Pelliccia (1982) models. These models poorly fit the data (i.e. R^2<0.30) while the model developed in this research fit the data actually (i.e. R^2=0.87) as shown in Figure 7-2.

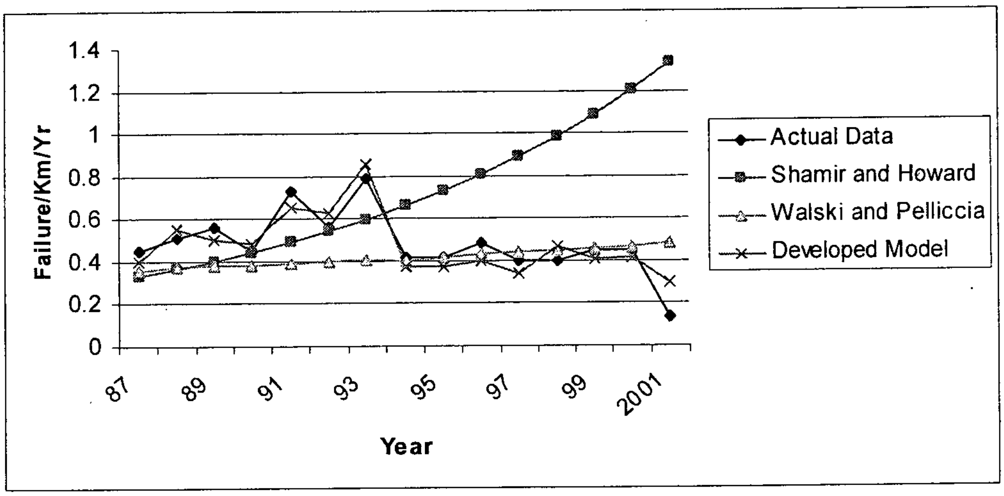


Figure 7-2: Applying Data on Existing and Developed Models

Selection of Best Subset

The purpose of using best subsets regression is to identify groups of predictors for further analysis. Ideally, one should select the smallest subset that fulfills certain statistical criteria (Minitab 2006). This is because a subset of predictors may actually estimate the regression coefficients and predict future responses with smaller variance than the full model that uses all predictors. The best subset regression was carried out by using Minitab software. Fifty trials were carried out to attain best results for available data. The best subset was selected to have the highest R^2 value, and relatively small Mallows C_P value. The selected subset in this study has R^2 of 89.1% and the Mallows C_P value of 9.1. It should be noted that smaller C_P value indicates relative preciseness of the model (has small variance) in estimating the regression coefficients and in predicting future responses.

Modeling Approach

Data-driven modeling approaches are gaining popularity due to the increasing availability of data in the water industry (Gibbs et al. 2006). Water utilities possess large quantities of data available from control and monitoring facilities. Statistical techniques can be applied to extract useful relationships from existing data sets, thus maximizing the utilization of the available data that are already available. The models presented in this paper utilize multiple regression and ANNs. ANNs are preferred due to their ability to handle nonlinearity and large amount of data, as well as their fault and noise tolerance, besides, ANNs have learning and generalization capabilities (Lawrence 1994). Two types of ANNs are applied, the Multi-Layer Perceptron (MLP) and the General Regression Neural Network (GRNN). The MLP is the most widely used type of network for forecasting and prediction applications (Maier et al. 2000). Thwin and Quah (2005) identified GRNN as a promising technique for building predictive models.

Multiple-regression is used as a benchmark to compare the performance of the ANNs can be compared.

Multiple-Regression Analysis

Regression analysis is performed using a 95% confidence level to calculate the regression coefficients. The regression coefficients were determined using 80% of the data set (560 patterns), and the coefficients found were implemented in the multiple-regression Equation (1) to predict the values in the validation data set (140 patterns).

According to available data and trials carried out the final regression equation is:

Failure Rate = 67.6 + 0.06 Length - 7.37 Ln (Length) - 2.34 Age + 0.028 $(\text{Age})^2$ + 11.07 Depth - 22.5 Ln (Depth) -0.0925 Temperature -0.05 $(\text{Temperature})^2$ +0.128 Precipitation **(7-1)**

Where the units of measurement of variables are given in brackets Length (m), Age (yr), Depth (m), Temperature (^{0}C), and Precipitation (mm)

Based on t-test results all t values > $t_{\alpha/2}$, which is 2.0306 and all p values < α, which is 0.05, the hypothesis H0 (βi=0) can be rejected, and Ha (βi ≠0) (i.e. one or more of the parameters are not equal to zero) is true. Based on Table 7-3, because the test statistic F= 509.2 > Fα= $F_{0.05}$ = 1.9384 and, p-value=0.000<α=0.05, which is the level of significance chosen for this study. A significant overall relationship is presented for the Model in Equation7-1. According to the above F- test and t- test results, the failure rate model has both an overall statistical significance and individual statistical significance (See Appendix E).

Table 7-3: Analysis of Variance

Source	DF	SS	MS	F	P
Regression	9	41611.5	4623.5	509.2	0.000
Residual Error	551	5006.7	9.08		
Total	560	46618.3			

Multi-Layer Perceptron (MLP) Model

Three layers MLP were used to develop this model input, hidden, and output layers, respectively. The number of neurons in the input layer equals the number of attributes in the feature vector (the aforementioned deterioration factors and their Box-Cox transformations). The output layer of the proposed network consists of one neuron, which represents failure rate/Km of cast iron water mains. The number of neurons that should be used in the hidden layer is decided by trial and error (Loony 1997; Tamura and Tateishi 1997; Haykin 1999; Moselhi and Sehab-Eldeen 2000). The commercially available neural network software package NeuroShell 2 is used for development of the model. The network uses the back-propagation algorithm to optimize connection weights. The transfer function in the input layer was determined to be linear [-1, 1], while the Gaussian and Hyperbolic Tangent (tanh) functions were used for the hidden layers and output layers, respectively. Cross-validation is used to determine when training should be stopped to prevent over fitting. Near optimal learning rates and momentum values were determined using a trial and error approach. Learning and momentum rates ranging from 0.05 to 0.3 were tested and he ntear optimum values were found to be 0.062 for the learning rate and 0.28 for the momentum value. The preliminary number of hidden neurons is selected using the following equation (NeuroShell-2 1996):

$$N = 0.5(X + Y) + (Z)^{0.5} \tag{7-2}$$

Where: N represents the number of neurons in the hidden layer; X is the number of input patterns; Y is the number of output patterns; and Z is the number of patterns in the training set.

The prepared data (700 patterns) are used in developing and validating the network. The total number of patterns was randomly divided as follows: 420 patterns (60%) for the training set; 140 patterns (20%) for the testing set and 140 patterns (20%) for the validation set. The validation set patterns were not used during the training or testing processes, but used to test the generalization capability of the trained network (i.e. the overall network performance).

General Regression Neural Network (GRNN) Model

GRNN is a three-layer network where there must be one hidden neuron for each training pattern. There are no training parameters such as learning rate and momentum as in the back-propagation, but smoothing factor was applied after the network is trained. GRNNs are known for their ability to train quickly on sparse data sets, and their applications are able to produce continuous valued outputs. GRNN is a type of supervised network especially useful for continuous function approximation (Neuroshell2, 1996; Mie and Tong 2005; Gibbs et al. 2006; Irwan et al. 2007). For the GRNN models, the training and testing data sets were combined to produce one calibration data set. The GRNN networks work by comparing patterns based upon their distance from each other, two methods of computing this distance were tested and it was found that the City Block method is computationally quicker but produced slightly less accurate predictions when compared to the Euclidean Distance method. Hence, due to the limited data and relatively fast run time, the Euclidean distance method was selected. A Genetic Algorithm (GA) was used to calibrate the multiple smoothing factor of the GRNN. A stopping criterion of 20 generations with no improvement of the mean squared error by at least 1% is used. The design and the generalization results obtained from the MLPNN and GRNN are summarized in Table 7-4.

Sensitivity Analysis

In an effort to improve the performance of the developed NN models, a sensitivity analysis was carried out to study the effect of the input attributes on the overall performance of the model. The general performance of the model was measured by the values of the coefficient of multiple determination (R^2) and residual errors (NeuroShell-2 1996). In this analysis, several trials were conducted with different combinations of input variables and their performances were compared. Based on the analysis of the results obtained, nine attributes were used in the input layer of the developed network, which was tested indicating a success rate of 89%. As shown in Figure 7-3 the study revealed that pipe length and age of pipe has a significant contribution to the failure rate, while, the pipe size(diameter) is excluded due to its insignificant contribution to the model.

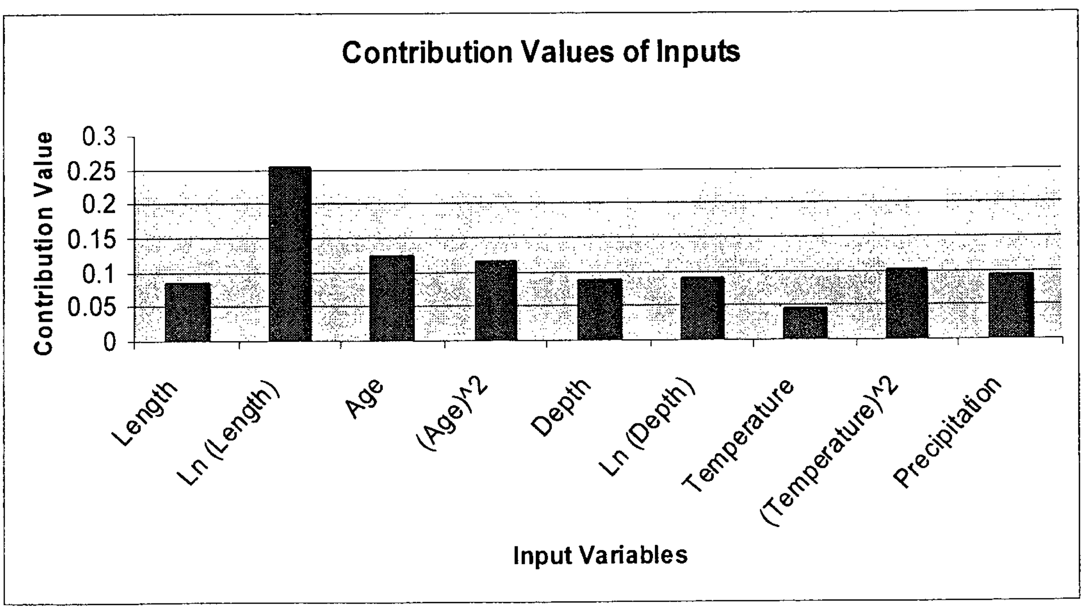
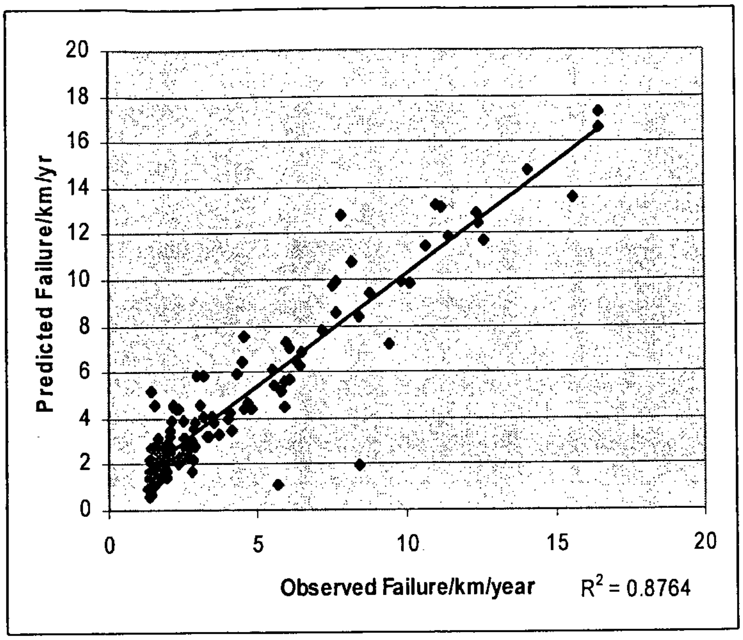


Figure 7-3: Contribution of the Final Input Variables Considered

Table 7-4: Comparison between Final MLPNN and GRNN

	MLPNN model	GRNN model
Input layer	9 input	9 input
Hidden layer	One hidden layer with 24 nodes	One hidden layer with 420 nodes
Output Layer	Failure/Km/yr	
Algorithm used for minimizing error	Steepest decent	Genetic Algorithm
Activation function(s)	Gaussian (hidden) and Hyperbolic Tangent (tanh)(output)	Gaussian
Dataset used in model development	3 municipalities in Canada over a period of 15 years	
Use of Dataset	60% training, 20% testing, and 20% generalization	
R^2 for test set	0.9485	0.9612
R^2 for generalization set (validation)	0.8764	0.8869
Mean absolute error	0.3724	0.3356
Max. absolute error	6.5001	6.5003
Min. absolute error	0.003	0.003

As shown in Table 7-4 and Figures 7-4, 7-5 and 7-6 the two NN models developed in this research have higher coefficients of determination than that of the models presented by Wong (2006) and Achim et al. (2007). Consideration of temperature and precipitation as input variables, account indirectly for factors that acts on the external surface of buried pipes such as corrosion, and external pressure arising from freezing soils.



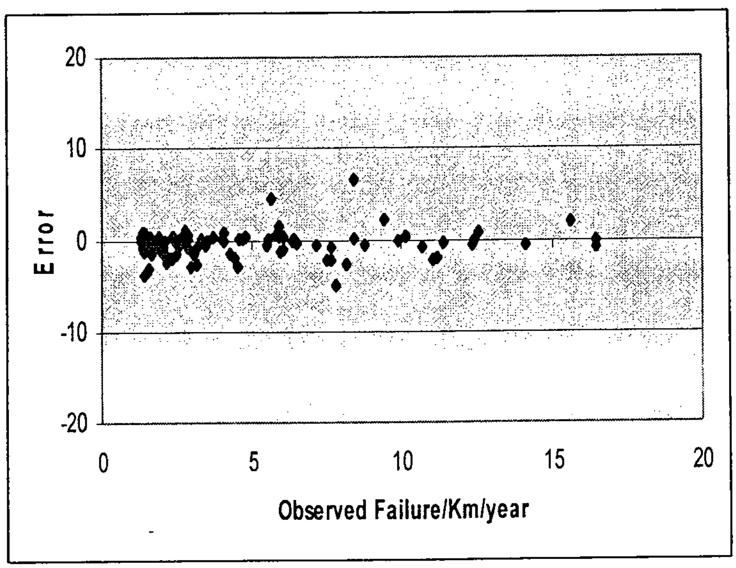
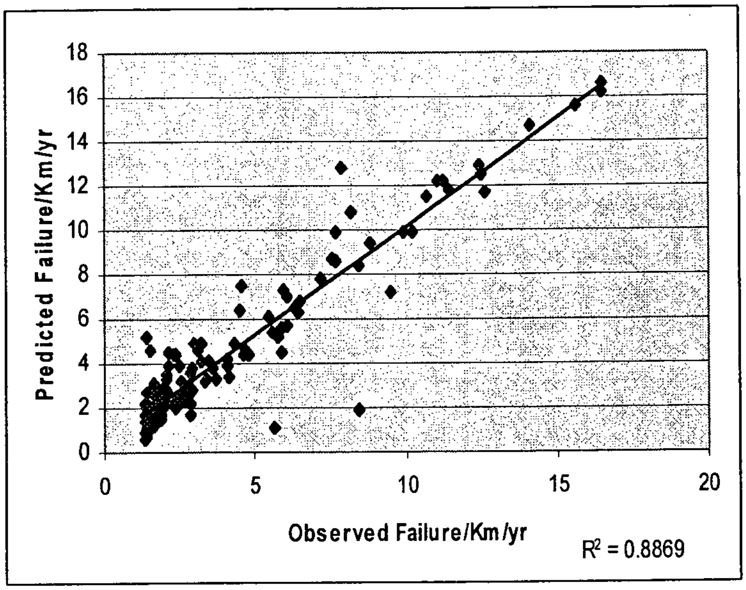


Figure 7-4: MLPNN model prediction versus observed sample

(a) Coeff. of multiple determination (R^2) (b) Residual Error



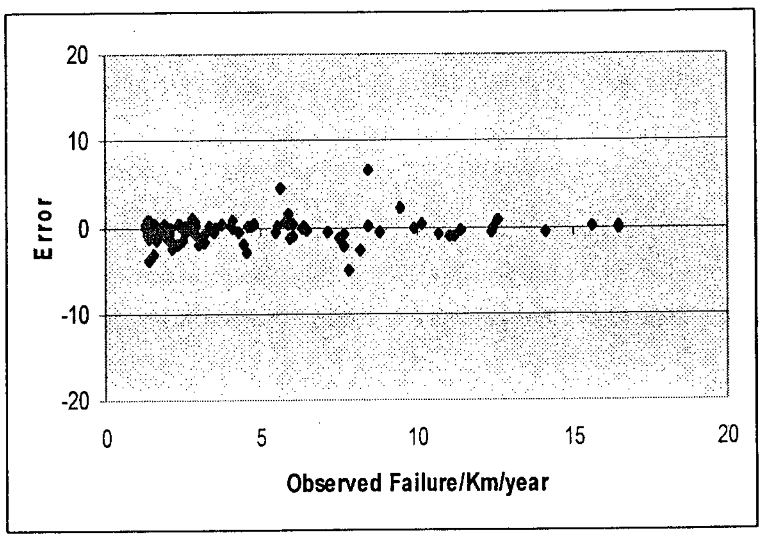


Figure 7-5: GRNN model prediction versus observed sample

(a) Coeff. of multiple determination (R^2) (b) Residual Error

Figure 7-6 depicts comparison between the results obtained from applying the three models developed in this research (Multiple-regression, MLPNN, and GRNN) versus the actual data and results obtained from Achim et al. model (2007) for a sample of 29 validation patterns. Detailed comparison between Achim et al. model and the model developed herein can be found in discussion by Moselhi and Fahmy (2008). As shown in Figure 7-6 the GRNN model developed in this research has the best fit of the actual data.

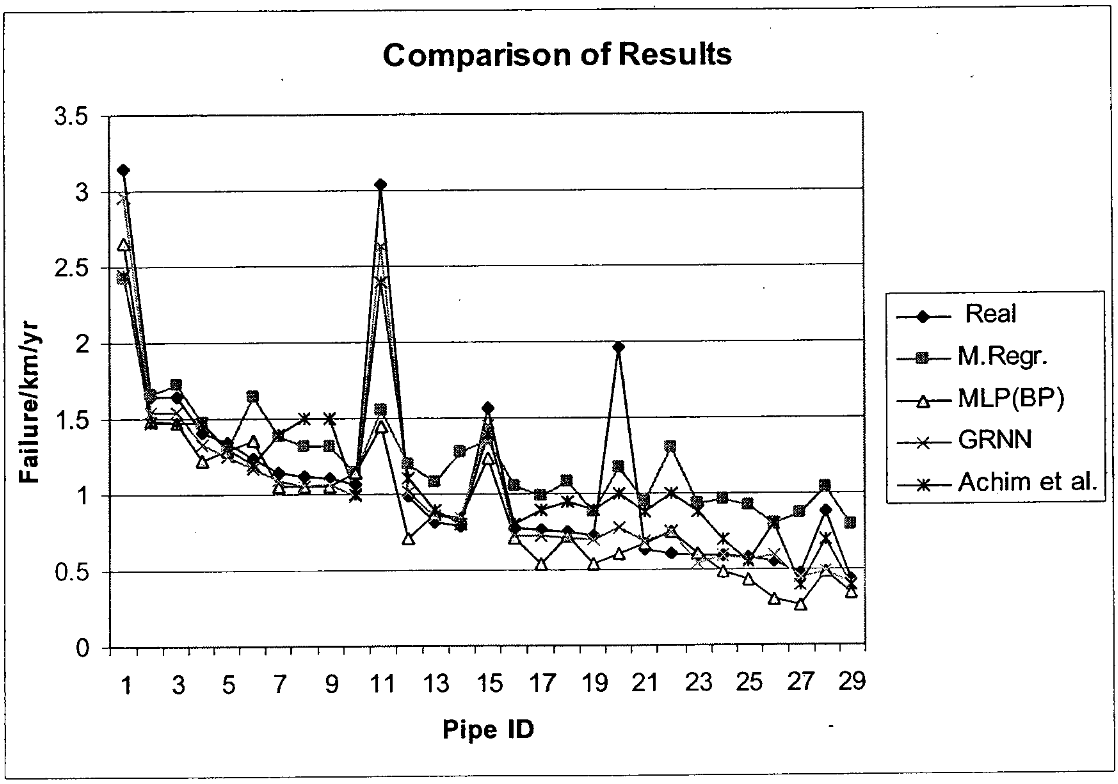


Figure 7-6: Comparison of Results

The outputs obtained from the selected GRNN model are automatically used in the determination of the condition rating of the pipe being studied as described by Moselhi and Fahmy (2007 and 2008), and depicted in Figure 7-7.

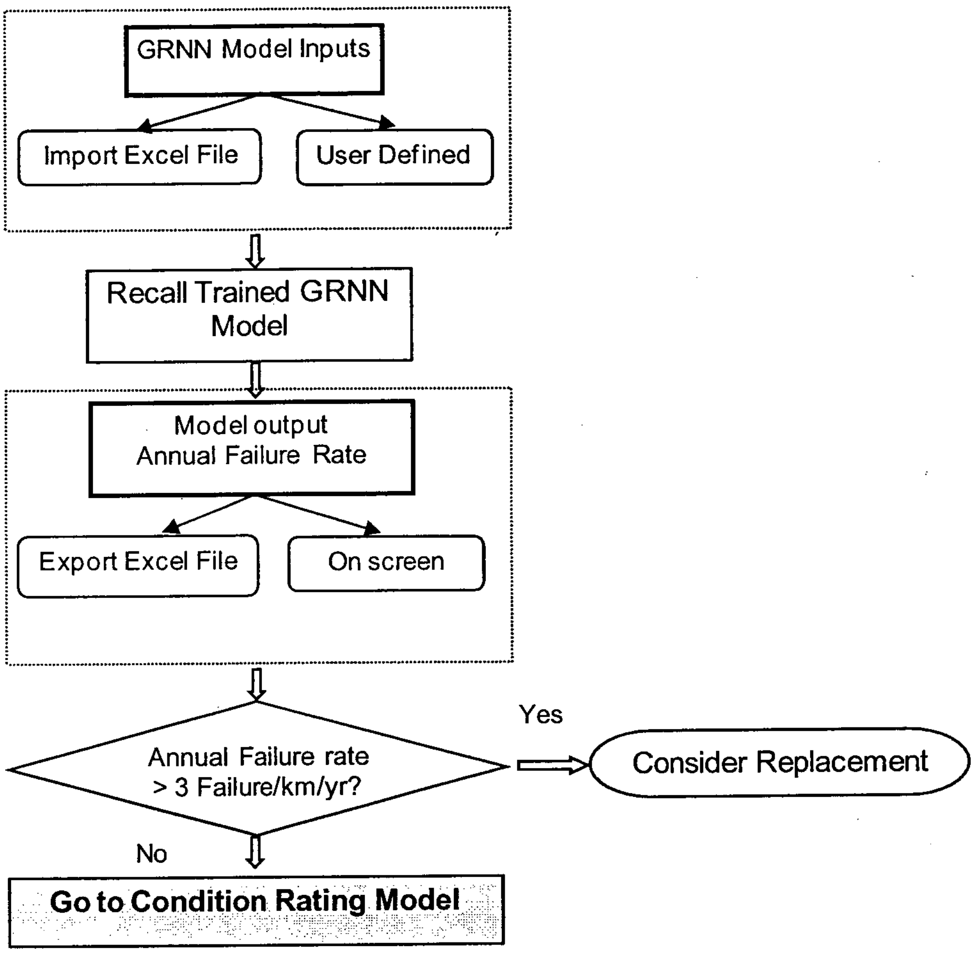


Figure 7-7: Model Input/ Output Diagram

7.6 Summary and Concluding Remarks

Three different data-driven techniques are used to investigate the relationship between failure rates of cast iron water mains and a set of deterioration parameters, and to predict failure rates of cast iron water mains. This includes two types of ANNs, the Multi-Layer Perceptron (MLP) and the General Regression Neural Network (GRNN). Multiple-regression was also used as a benchmark against which the performance of the ANNs was compared. A 15-year data set containing routinely measured parameters is used for model development and validation.

The study revealed that GRNN model presents the best fit to the actual data; therefore, the GRNN model was selected to represent the model. The outputs from the model are used automatically in condition rating of pipe(s) being considered as described by (Moselhi and Fahmy 2007 and 2008).

Despite the difficulties in obtaining reliable source data, the model presented herein demonstrated a satisfactory performance when compared to existing models (R^2=88%). The model could be applied to single pipe as well as a group of pipes. Furthermore, using external environment factors such as ambient temperature and precipitation as input variables would be a platform for a generic model that could be applied in different places around the globe. An improvement of the model performance would be found in considering other factors that influence pipe deterioration such as soil condition, which is implicitly considered in pipe age and not considered as an independent variable in model development due to the lack of information about soil types and its condition.

CHAPTER 8

Condition Rating and DSS for Recommending Maintenance/Rehabilitation Action

8.1 Model Design and Development

The design and development of model involved three main stages: 1) Identifying factors that affect the condition rating of water mains; 2) Modeling of condition rating; and 3) Integrating this model with the other models that were designed and developed in this research into the prototype software system, namely, Water Mains Management System (WMMS) to demonstrate the capabilities and essential features of the developed models. The three stages of the model design and development are described below.

Identifying Factors Affecting Condition Rating of Water Mains

A set of factors were identified based on the field investigation, interviews with experts, and extensive literature review. The identified factors were used for development of the condition-rating model. Table 8-1 lists the factors that were used for development of the model and it should be noted that these factors are beyond those considered in existing condition rating models developed by others (Refer Chapter 2 Literature Review section).

As depicted in Figure 8-1 the developed condition-rating model utilizes distress indicators for condition rating that are based on outputs generated from the three models developed using the research and described in previous chapters. The model also uses hydraulic, socioeconomic and maintenance factors additionally. The attributes of socioeconomic factors include type of customer, population density and risk of break consequences (location of the main), whereas the attributes of the maintenance program include condition of associated valves, cathodic protection program, and regular cleaning and flushing rates. Hydraulic attributes include internal lining condition, and tuberculation % or C- factor (Hazen-William Coefficient).

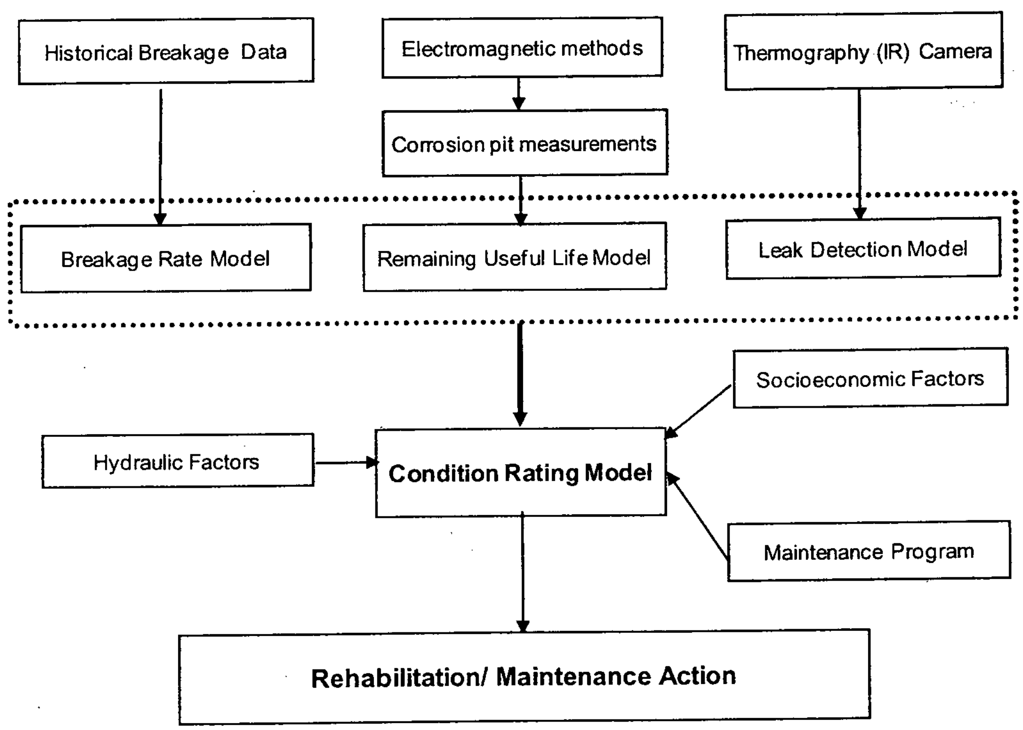


Figure 8-1: Layout of the Developed Condition Rating Model

Table 8-1: Factors Affecting Condition Rating of Water Mains

Condition Rating Factors	Limits
Remaining Useful Life	0-100 yr
Annual Breakage Rate	0-5 break/km/yr
Leak condition	Low (10Lit/km/day) -Medium-High (450Lit/km/day)
Hydraulic factors: -Internal lining condition - C- factor (Hazen-William Coefficient.) -Tuberculation %	0-100% defected 30-100 0-80%
Socioeconomic Factors: - Include type of customer - Population density - Risk of break consequences	Residential-Commercial- VIPs Rural-sub-urban-city In main road-not in road way
Maintenance program Factors: -Associated valves condition -Cathodic protection program -Regular cleaning and flushing	10-90% from good condition 0-80% from well defined program 0-100% well defined program

8.2 Modeling of Condition Rating

The developed model follows a hierarchal structure and was developed using priority index for rehabilitation plans. As can be seen from Figure 8-2, the decision hierarchy used in the application of AHP consists of three levels; providing increasingly detailed definition towards the lowest level.

As shown in Figure 8-3 the model uses the output results from the three indigenous models of this research (Leak detection and identifying its location model, forecasting the remaining useful life of the considered pipeline model, and predicting annual failure rate of the considered pipeline model). The output obtained from each model is examined for failure criterion, if the output value is above the threshold failure value, replacement is considered. If, however, the output value obtained from the three models are below their respective threshold failure values, the outputs will be used along with the other three factors shown in Table 8-2 are used to generate a composite index about the condition of the water main being assessed, and then used to generate a priority index for rehabilitation plans. The model was integrated with a prototype software system namely WMMS through a set of interactive questions; the developed software system can automatically generate the priority index associated with each attribute in the decision criteria. Figure 8-4 shows a sample of such priority indices.

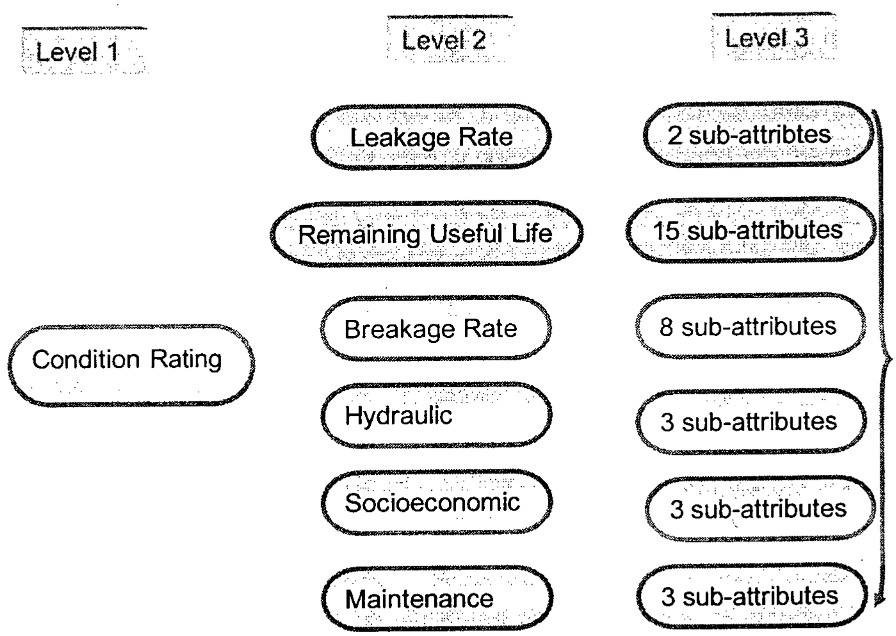


Figure 8- 2: The Analytical Hierarchy Structure of the Condition Rating Model

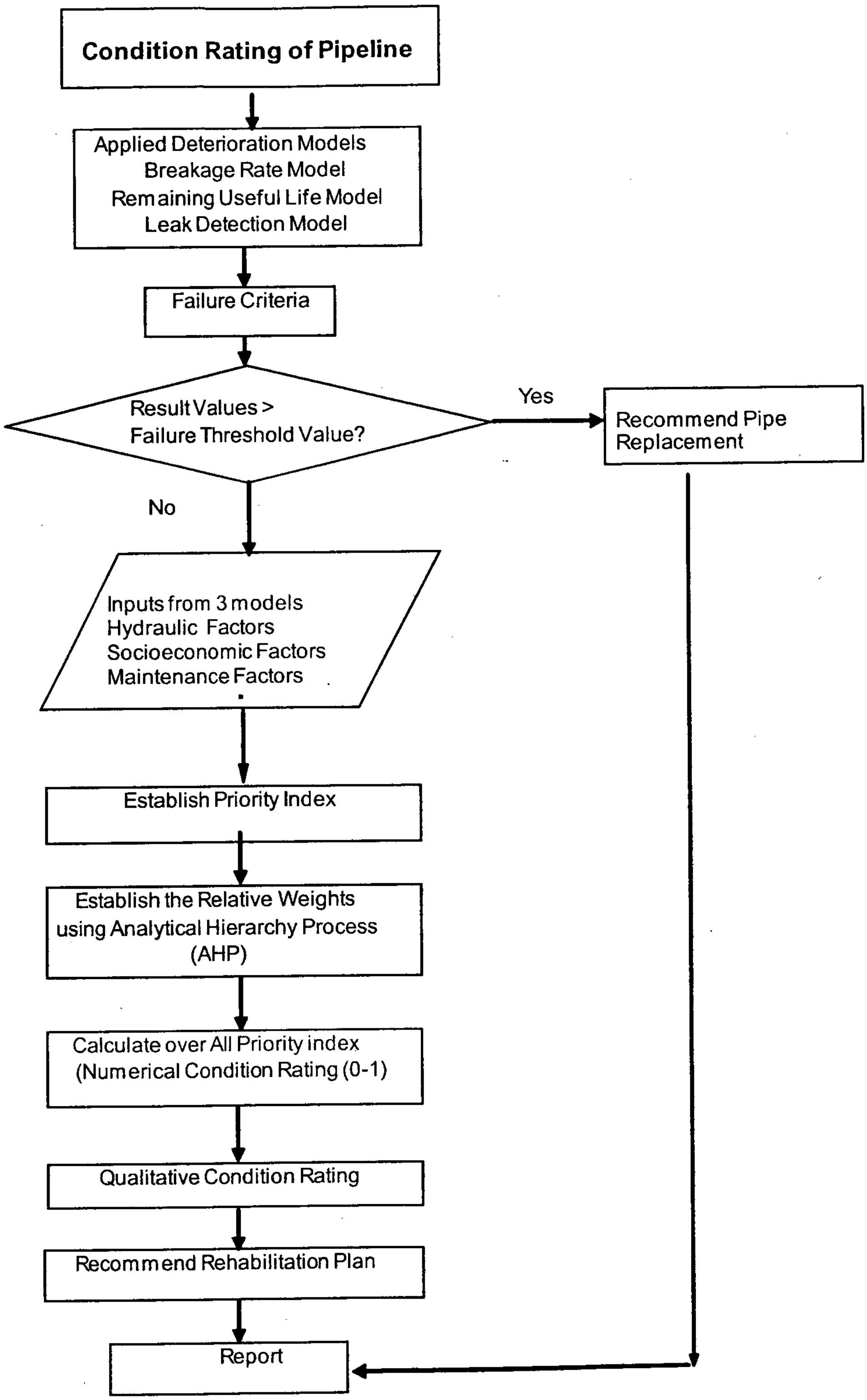


Figure 8-3: Flow Chart for Model Methodology

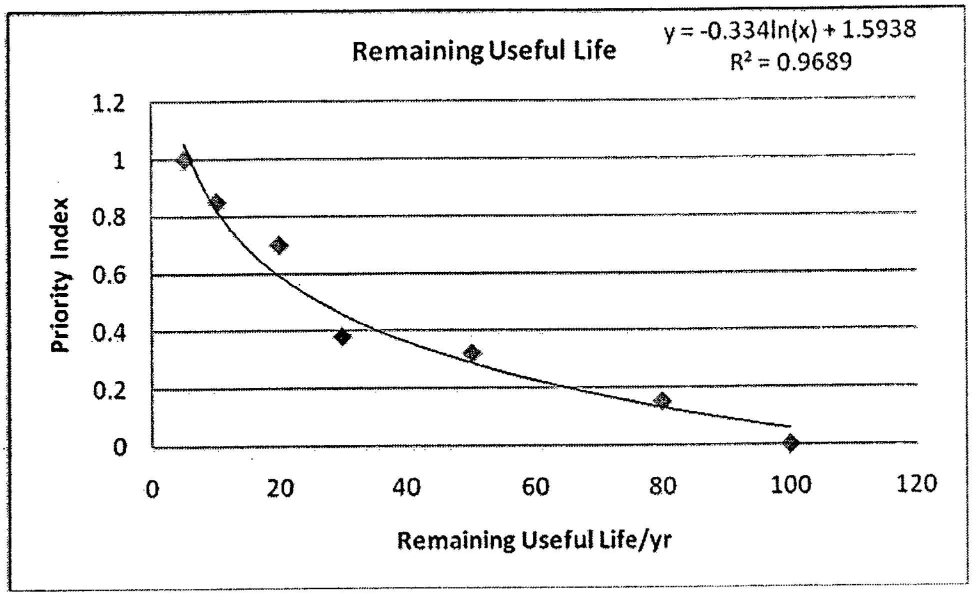


Figure 8-4: Priority Index Function for Remaining Useful Life

The implementation of the priority index functions and the suggested priority index values of the attributes were acquired from interviews with experts (Al-Barqawi 2006, Bourgeois 2006, Loiacono 2006, and Salvo 2006), and from a comprehensive literature review (Clark et al. 1982; Randall et al. 1992; Boyce 1994; Baer 1998; Kleiner and Rajani 1999, 2000, 2001, 2002 and 2004; Kleiner et al. 2001; AWWA 2001; De Silva et al. 2002; OFWAT 2002; Stone et al. 2002; Dillon and Harfan 2002; Infra Guide 2003 (a and b); National Guide 2003 (a, b, c, and d).

The results of the study show that while the initially considered three factors pertaining to hydraulic attributes are dependent and C-Factor can represent the remaining two factors. In addition, the initially considered three factors pertaining to socioeconomic attributes are dependant and population density can represent the remaining two factors. In addition, the initially considered three factors pertaining to maintenance program are dependent, and can be represented as a percentage of well-defined program. Table 8-2 shows the values of priority indices or range of values for the factors considered finally. Figure 8-5 shows the calculation of priority index values for a pipe being studied.

Table 8-2: Factors and the Range of their Respective Values

Condition Rating Factors	**Range for Considered Values**	**Priority Index (0-1)**
Remaining Useful Life	0-100 yrs	*Descending
Annual Breakage Rate	0-5 break/km/yr	Ascending
Leak condition	10-450 Lit/km/day	Ascending
Hydraulic factor(C- factor (Hazen-William Coefficient.)	0-120	*Descending
Socioeconomic Factor (Population density)	Rural-Sub-Urban-City	Ascending
Maintenance program Factor	0-100% (well defined program)	Ascending

* Descending from 1 to 0

The user is required to assign the relative weights representing the relative importance of the attributes being considered. This is carried out using the analytical hierarchy process based on pair- wise comparisons among the various attributes being considered (Figure 8-6 a and b). To insure the accurate selection of relative weights, the analytical hierarchy process measures the overall consistency of judgments by means of a **C**onsistency **R**atio (CR). The calculation of the CR is given in Appendix B; however, the prototype software developed calculates the Consistency Ratio automatically. If the CR is less than or equal to 10%, the software prompts the user to proceed further, but if the CR is greater than 10%, the software will prompt the user to revise the relative weights in the pair- wise matrix and repeat the process. The recommended average weights are shown in Figure 8-6 and more details about the same can be found in Appendix F.

Once the required input information described above is fed into the system, it calculates the overall priority index value of each alternative based on the following equation:

$$U_i=\sum_{J=1}^{n} W_j\, U_{ij} \qquad \textbf{(8-1)}$$

Where:

U_i: overall priority index value representing condition rating of the pipe

W_j: The relative weight assigned to the j^{th} attribute

U_{ij}: The priority index value of the j^{th} attribute associated with the i^{th} condition rating being considered.

The study also revealed that the priority index value for each attribute could be calculated based on the actual condition of the considered water main during evaluation process. The equations used in the system are listed in Appendix F.

The overall priority index value represents the condition rating of the pipe being considered. It ranges from 0 to 1; where "0" represents very good condition (i.e. no immediate action is required) and "1" represents failure that requiring immediate action (pipe replacement), see Table 8-4.

Table 8-3: Proposed Condition Rating

Overall priority index value	Condition rating
< 0.20	Very Good
0.20-0.39	Good
0.40 – 0.59	Average
0.60-0.79	Poor
>0.80	Fail

After determining the condition rating of the pipe, the system suggests a maintenance plan and recommends most suitable rehabilitation method. The system provides the user with a final report that includes the results of the condition-rating model and the recommended action plan. A sample of the system-generated report is shown in Table 8-5

Table 8-5: Proposed Condition Rating and Associated Maintenance Action

Condition Rating Scale	**Condition Rank**	**Criteria**	**Recommendations**
< 0.20	V.Good	Remaining useful life>80 yr; breakage rate < 0.5 Break/km/yr; Water quality 9-10, C- factor >100, Low population density, well defined maintenance program,	-Regular cleaning and flushing -Monitoring Cathodic protection

8.3 Prototype Software

A prototype software Water Main Management System (WMMS), was developed to provide a tool for quantifying the impact of deterioration factors on condition rating of CI water mains. The software incorporates: 1) the newly developed condition rating model; and 2) previously developed models by authors for condition assessment of water mains. The system was implemented using Microsoft Visual Basic as a stand-alone application that runs on Microsoft Windows 1998, 2000, and XP. To facilitate data entry and reporting, a set of user-interactive screens was developed as shown in the following case example.

8.4 Case Study

Consider a CI water main pipeline of length 800 m experiences leaks at different locations, that pipeline is located in commercial area of the city, and the municipality asks for performing a condition assessment work on that pipeline in order to select a suitable rehabilitation plan. Other information about this water main is shown in Table 8-6.

Table 8-6: Information of Pipe Condition

Attributes	Value
Estimated useful Life	80 yr
Predicted breakage Rate	0.5 Break/km/yr
Maintenance Program	80% Well defined
C-Factor	90
Population Density	High (City)
Leakage rate at joint	Low

Following the process previously described, the system provides the user with the condition rating along with the recommended maintenance or rehabilitation plan as shown in Figure 8-7.

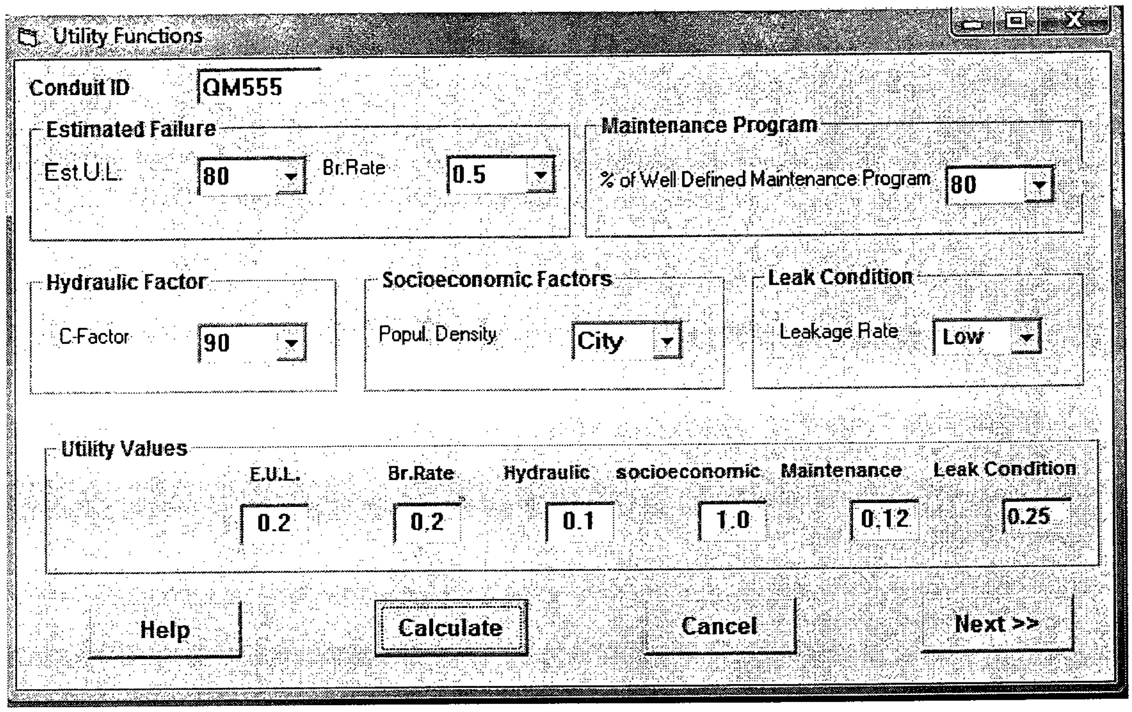


Figure 8-5: Calculation of Priority Index Value

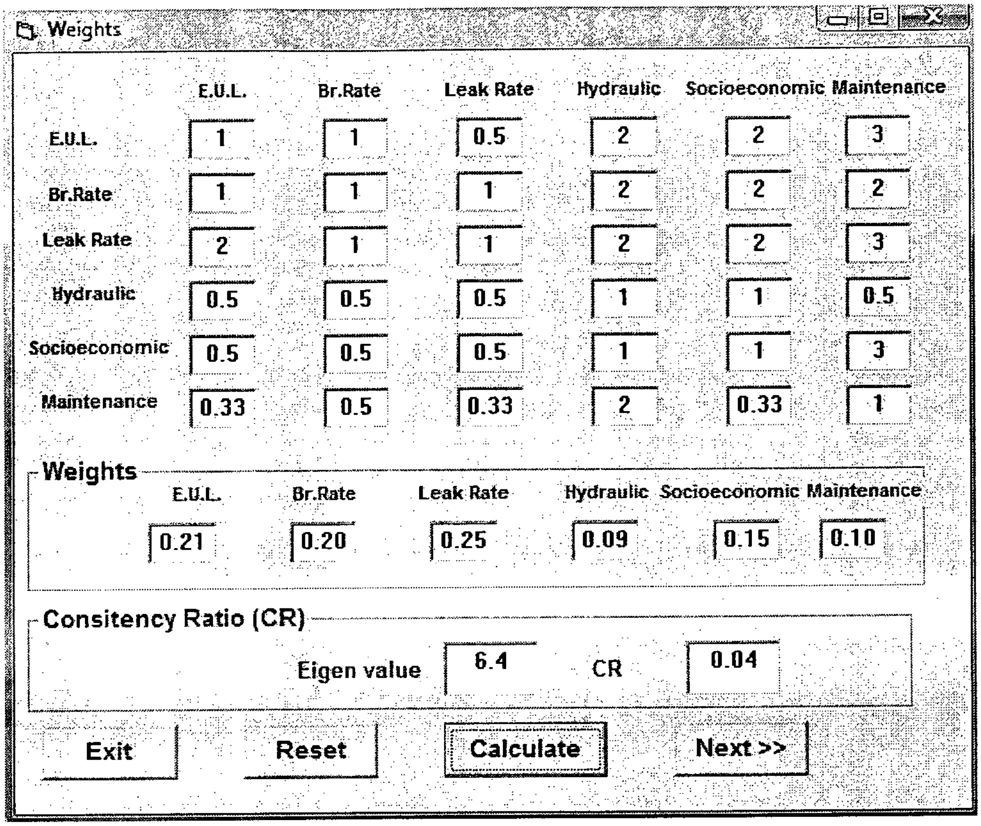


Figure 8-6 (a): Calculations of Weights

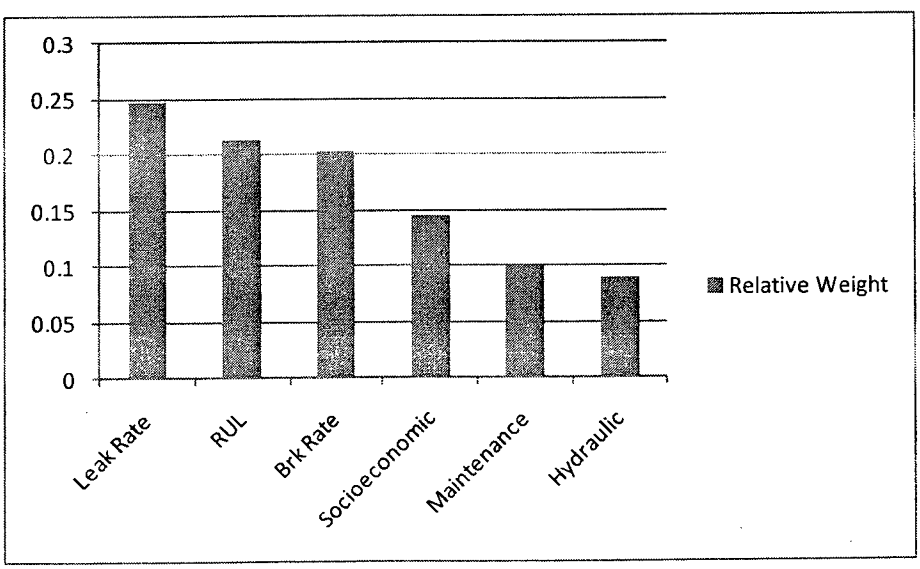


Figure 8-6 (b): Relative Weights

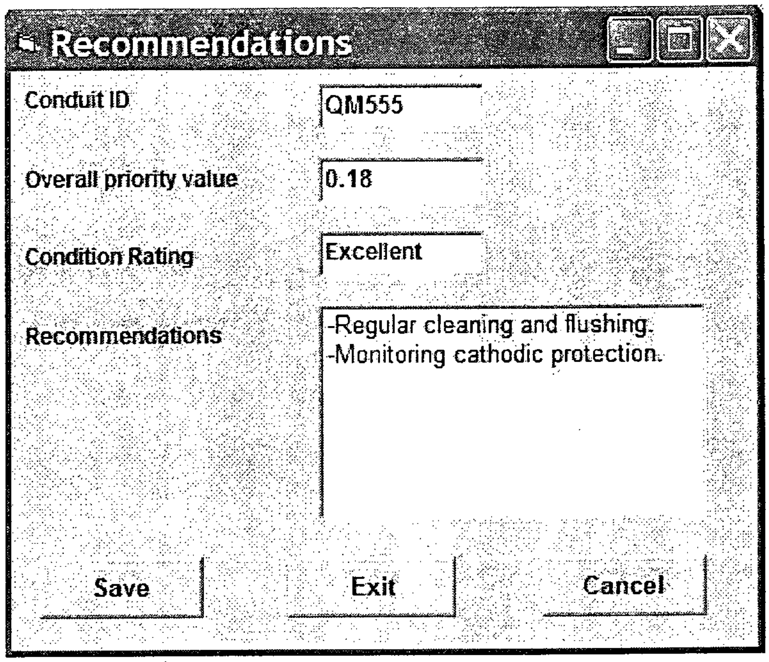


Figure 8-7: Condition Rating Results and Recommendations

8.5 SUMMARY AND CONCLUDING REMARKS

A condition-rating model for evaluating the condition of CI water mains is presented. The model follows a hierarchal structure and was developed based on priority index functions. Thirty factors initially considered in model development grouped under physical, environmental, operational, socioeconomic, and maintenance factors (besides the factors considered in already existing models). The model provides more comprehensive evaluation of the pipe under consideration. The developed model implemented in prototype software, which provides a user interface screen to facilitate the use of the model. The model is designed to be flexible enough to accommodate further factors. A case study presented at the end demonstrates the capability and essential feature of the model.

CHAPTER 9

SUMMARY AND CONCLUDING REMARKS

9.1 Summary

This research presents a methodology that aims at enhancing the current practice of condition assessment of water mains. The developed methodology integrates newly developed models and DSSs that are based primarily on non-destructive evaluation and rehabilitation methods provides a wide range of alternatives for decision makers, and transfers the knowledge gained to municipal engineers, eventually facilitating the decision-making process in managing water mains, and providing a comprehensive decision for the selection of appropriate evaluation and rehabilitation methods. The proposed methodology is hierarchal in structure and is based on intensive literature review, interviews with experts, field investigation, and experimental work. It integrates five newly designed and developed models and sub-systems. It is also implemented in a prototype software system namely Water Mains Management System (WMMS) as a proof of concept, which could demonstrate the capabilities and essential features of the developed methodology. WMMS is hierarchal in structure and integrates the following models and subsystems:

1) designed and developed DSS for selecting most suitable method of inspecting water mains; 2) designed and developed automated system for detecting water leaks in underground pipelines and determine their respective

location; 3) designed and developed two models for estimating remaining useful life and predicting annual failure rate of CI water mains; and 4) condition-rating model, and DSS for recommending rehabilitation/maintenance plan

An explanation of the implementation of each model and sub-system is described separately, including data acquisition, preparation, analysis, modeling and validation.

Case examples are provided to demonstrate the use and benefits of the newly developed models.

9.2 Research Contributions

Current research contributed, to the state-of-art for condition assessment of water mains. It provides a framework for municipal engineers and researchers to assist them in evaluation and prioritizing rehabilitation/ maintenance actions for existing water mains. These contributions of the research are listed below.

1. Analysis of existing condition assessment methods and existing models, in addition to identifying their limitations for proactive condition assessment and reactive failure detection.
2. Field investigation and experimental work to compare acoustic- based leak detection method and thermography (IR) camera system.
3. Design and development of a DSS to assist in selection of most suitable non- destructive evaluation method(s) for condition assessment of water mains.
4. Design and development of model to detect water leaks and identify their respective locations using thermography (IR) camera.

5. Design and development of model for estimating the remaining useful life of CI water mains.
6. Design and development of model to predict the failure rate of CI water mains.
7. Design and development of model for condition rating and DSS for prioritizing and recommending maintenance/ rehabilitation actions of CI water mains.
8. Implement the developed methodology in a prototype software system as a proof of concept, which could demonstrate the capabilities and distinguishing features of the developed methodology.

9.3 Limitations and Recommendations for Future Researches

1- The data utilized in implementing the DSS for selecting most suitable inspection method is limited to methods available in some cities located in North America and Europe. It is also based on average cost that may vary based on location of application. Therefore, it is recommended to expand and update the DB to be matched with location of water main being tested. In addition, adding new methods as they become available.

2- Although the field investigation for detection of water leaks using IR camera provides satisfactory results, it is restricted to the type of soil and pavement in city of Montreal and its weather. Lab models and experiments are recommended in order to save time and consequently cost by controlling the environment surrounding the pipe being tested, including type of soil, its degree of saturation, pavement material, prevailing light and weather

3- Expanding the study by mounting the IR camera system on airplane for detection of long pipeline, this study is limited to scanned pipeline with maximum length of 300 m.

4- Utilizing the GIS technology to detect and locate water leaks can enhance the accuracy of results and augment the automation of the developed model.

5- The estimating useful life model is limited to CI water pipes with size 6"-8", and data collected from 16 cities in NA, more data are required for different types of pipelines, which are located elsewhere.

6- The breakage rate model is limited to CI water pipes with size ranged from 150 mm to 200 mm , and historical data collected from three cities in Canada, more date are required for different types of pipelines that are located elsewhere, including information about surrounding environment in order to augment the reliability of the model

7- The recommendations of maintenance/rehabilitation action used in the developed DSS are based on methods used in some cities located in NA, and UK, therefore, expanding the knowledge base about methods applied elsewhere and updating the system with those methods along with their allocated budget cost would enhance system reliability.

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Appendix A

Appendix A-1: Common Non-Destructive Evaluation Methods

Method	Advantages	Disadvantages
Zone Water Audits	• cheap • covers large areas of a city quickly • allows for a comparison of water losses between individual districts • useful as a screening process for other techniques • can be used to evaluate the effectiveness of repair programs	• does not give the precise location of leaks • requires isolation of zones • work must be performed at night • only gives an overview of current problems
Sonic/Acoustic Leak Detection	• widely practised • known to find leaks accurately • known to find leaks of different sizes • operates from outside the water line	• percentage of leaks missed by the technique is unknown • currently works best in metal water lines • only gives information on the current condition of the line (the tool has little predictive value) • background noise problems
Remote Field Inspection	• most advanced technique currently available • detects areas of corrosion pitting, as well as through holes • can be used to give an estimate of the future life of a line	• more expensive than leak detection • requires access to the inside of the water line, which may require cleaning • knowledge of the relationship between pit size and residual life of the pipe is not yet complete • model evaluated by NRC would not detect pits of less than 3000 mm3 in size.
Magnetic Flux Leakage	• established technology in oil and gas industry • known to be capable of detecting small defects and through holes in steel pipe	• not yet commercially available for water lines • requires access to and complete cleaning of the inside of the pipe
Ultrasound	• most versatile NDE technique • established technology in oil industry • NRC tests show that it can detect and size corrosion pitting • Technique will not work through tuberculation	• not yet commercially available for water lines • requires access to and complete cleaning of the inside of the pipe

Appendix A-2: Common Water Main Materials (National guide2003).

Pipe Material	*Range of Diameter*	*Period of Installation*	*CSA Standard*	*AWWA Standard*	*AWWA Manual*
Pit Cast Iron (CI)	75-1,500 mm	1850s-1940s	-	C100[1]	-
Spun Cast Iron (CI)	75-1,500 mm	1930s-1960s	-	C100[1]	-
Ductile Iron (DI)	75-1,600 mm	Since 1960s	-	C151	M41
Steel	> 150 mm	Since 1850s	Z245.1	C200	M11
Polyvinyl Chloride (PVC)	100-1,200 mm	Since 1970s	B137.3	C900/905	M23
High Density Polyethylene (HDPE)	100-1,575 mm	Since 1980s	B137.1	C906	-
Asbestos Cement (AC)	100-1,050 mm	1930s to 1980s	-	C400	-
Concrete Pressure Pipe (CPP)	250-3,660 mm	Since 1940s	-	C300/301/302/303	M9

[1] British standard cast iron pipe is also common in Canada.

Appendix A

Appendix A-3: Factors that Contribute to Water System Deterioration (National guide 2003).

	Factor	Explanation
Physical	Pipe material	Pipes made from different materials fail in different ways.
	Pipe wall thickness	
	Pipe age	Effects of pipe degradation become more apparent over time.
	Pipe vintage	Pipes made at a particular time and place may be more vulnerable to failure.
	Pipe diameter	Small diameter pipes are more susceptible to beam failure.
	Type of joints	Some types of joints have experienced premature failure (e.g:, leadite joints).
	Thrust restraint	Inadequate restraint can increase longitudinal stresses.
	Pipe lining and coating	Lined and coated pipes are less susceptible to corrosion.
	Dissimilar metals	Dissimilar metals are susceptible to galvanic corrosion.
	Pipe installation	Poor installation practices can damage pipes, making them vulnerable to failure.
	Pipe manufacture	Defects in pipe walls produced by manufacturing errors can make pipes vulnerable to failure. This problem is most common in older pit cast pipes.
Environmental	Pipe bedding	Improper bedding may result in premature pipe failure
	Trench backfill	Some backfill materials are corrosive or frost susceptible.
	Soil type	Some soils are corrosive; some soils experience significant volume changes in response to moisture changes, resulting in changes to pipe

		loading. Presence of hydrocarbons and solvents in soil may result in some pipe deterioration.
	Groundwater	Some groundwater is aggressive toward certain pipe materials.
	Climate	Climate influences frost penetration and soil moisture. Permafrost must be considered in the north.
	Pipe location	Migration of road salt into soil can increase the rate of corrosion.
	Disturbances	Underground disturbances in the immediate vicinity of an existing pipe can lead to actual damage or changes in the support and loading structure on the pipe.
	Stray electrical currents	Stray currents cause electrolytic corrosion.
	Seismic activity	Seismic activity can increase stresses on pipe and cause pressure surges.
Operational	Internal water pressure, transient pressure	Changes to internal water pressure will change stresses acting on the pipe.
	Leakage	Leakage erodes pipe bedding and increases soil moisture in the pipe zone.
	Water quality	Some water is aggressive, promoting corrosion
	Flow velocity	Rate of internal corrosion is greater in unlined dead-ended mains.
	Backflow potential	Cross connections with systems that do not contain potable water can contaminate water distribution system.
	O&M practices	Poor practices can compromise structural integrity and water quality.

Appendix A

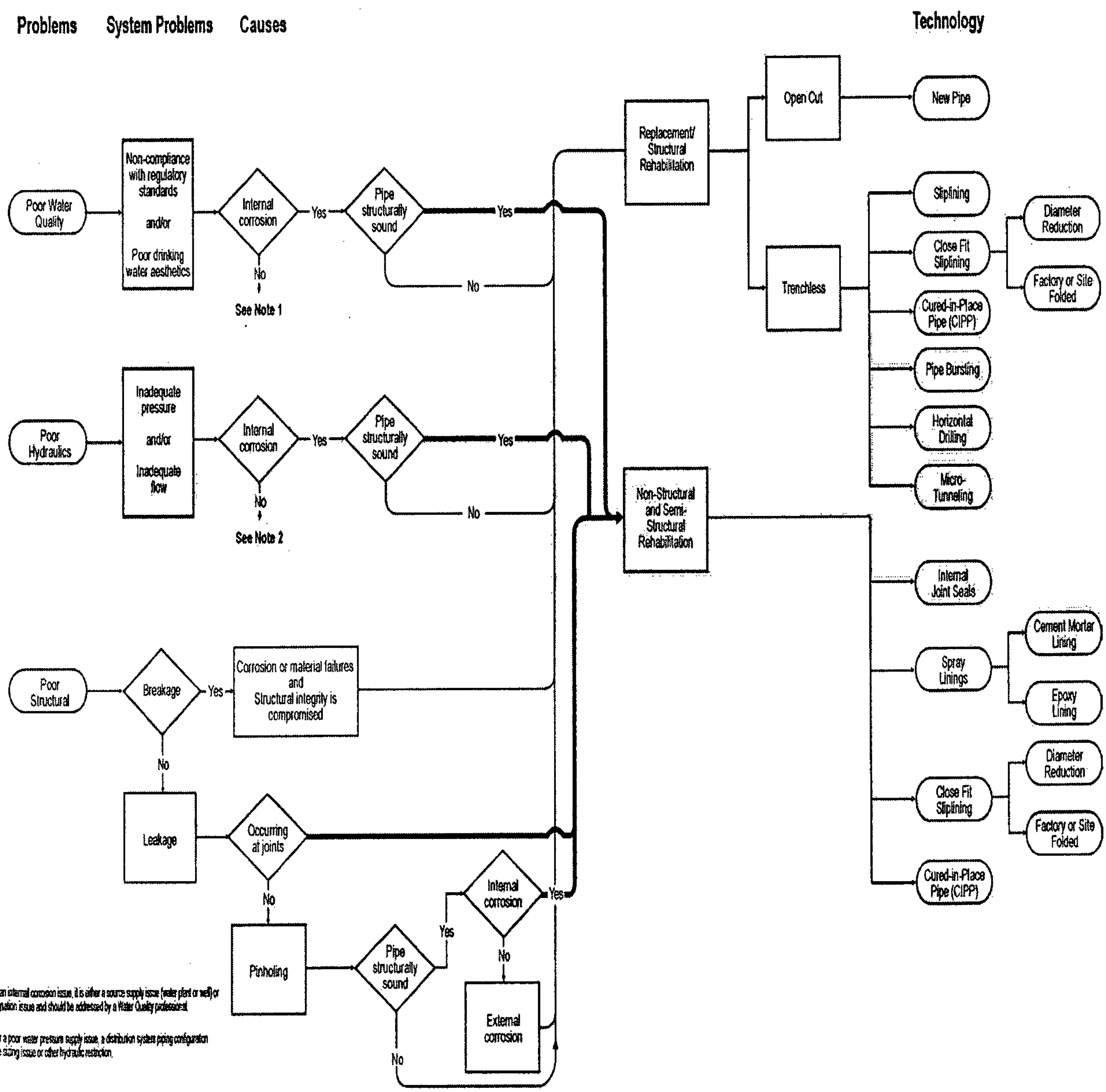
Appendix A-4: Structural Failure Modes for Common Water Main Materials (National guide2003).

Water Main Material	Structural Failure Modes
Cast Iron (CI)[1]	
Small diam (<375 mm)	• Circumferential breaks, split bell, corrosion through holes
Large diam (>500 mm)	• Longitudinal breaks, bell shear, corrosion through holes
Medium diam (375-500 mm)	• Same as small, plus longitudinal breaks and spiral cracking, blown section
Ductile Iron (DI)	• Corrosion through holes
Steel	• Corrosion through holes, large diameter pipes are susceptible to collapse
Polyvinyl Chloride (PVC)	• Longitudinal breaks due to excessive mechanical stress • Susceptible to impact failure in extreme cold condition (i.e. far north)
High Density Polyethylene (HDPE)	• Joint imperfections, mechanical degradation from improper installation methods, susceptible to vacuum collapse for lower pressure ratings
Asbestos Cement (AC)	• Circumferential breaks, pipe degradation in aggressive water • Longitudinal splits
Concrete Pressure Pipe (CPP)	• Pipes with pre-stressed wires may experience ruptures due to loss of pre-stressing upon multiple wire failure. • Pipe degradation in particularly aggressive soils, corrosion of pipe canister, concrete damage due to improper installation methods .

Appendix A

Appendix A-5: Selecting Appropriate Technologies for Rehabilitation or Replacing a Water Main (National guide 2003).

Selecting Appropriate Technologies for Rehabilitating or Replacing a Water Main FLOW DIAGRAM



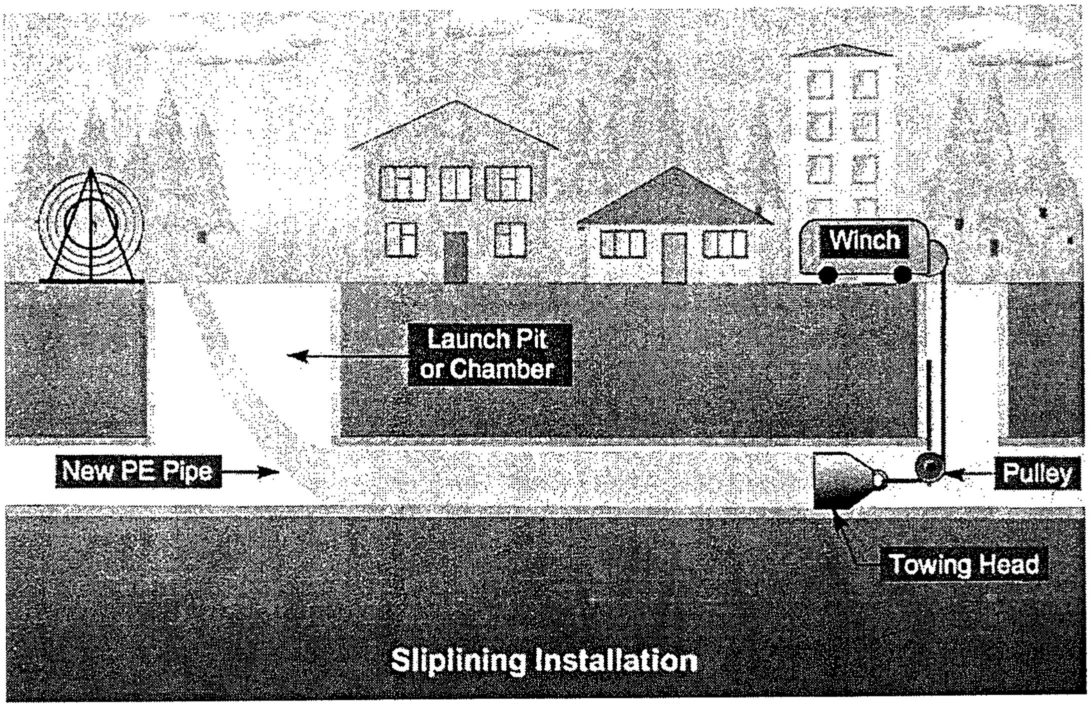
Notes

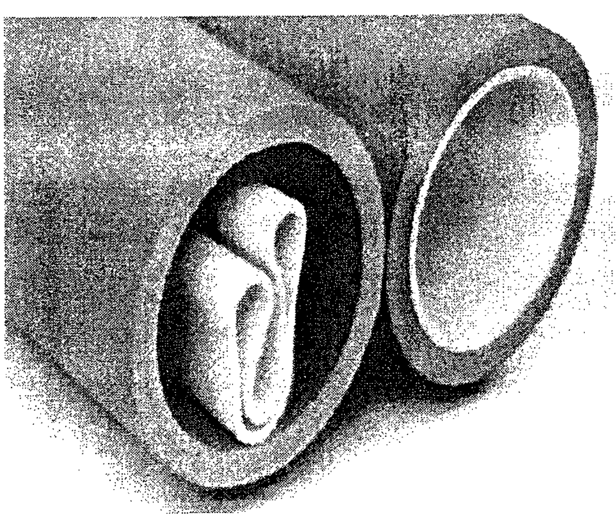
1. If this is not an internal corrosion issue, it is either a source supply issue (water plant or well) or a water stagnation issue and should be addressed by a Water Quality professional.

2. This is either a poor water pressure supply issue, a distribution system piping configuration issue, a pipe sizing issue or other hydraulic restriction.

Appendix A

Appendix A-6: illustration of some trench less techniques (National guide2003).

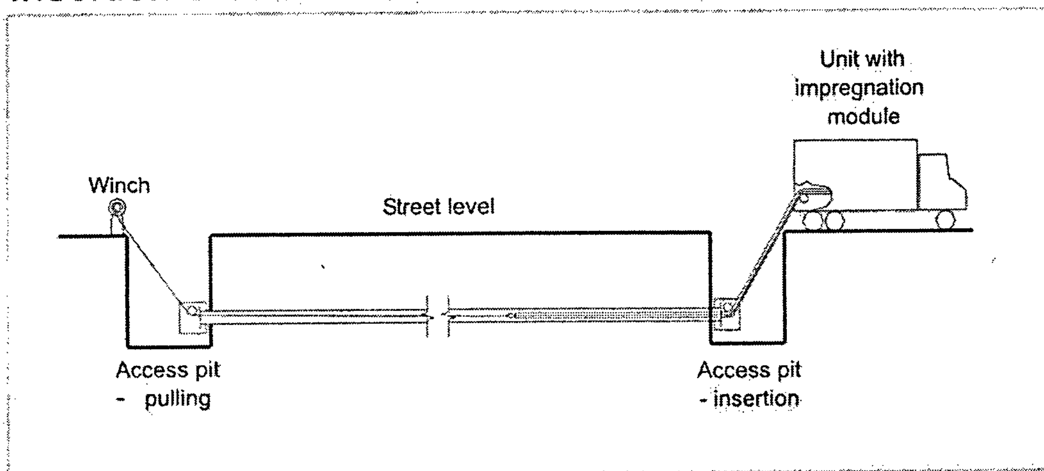




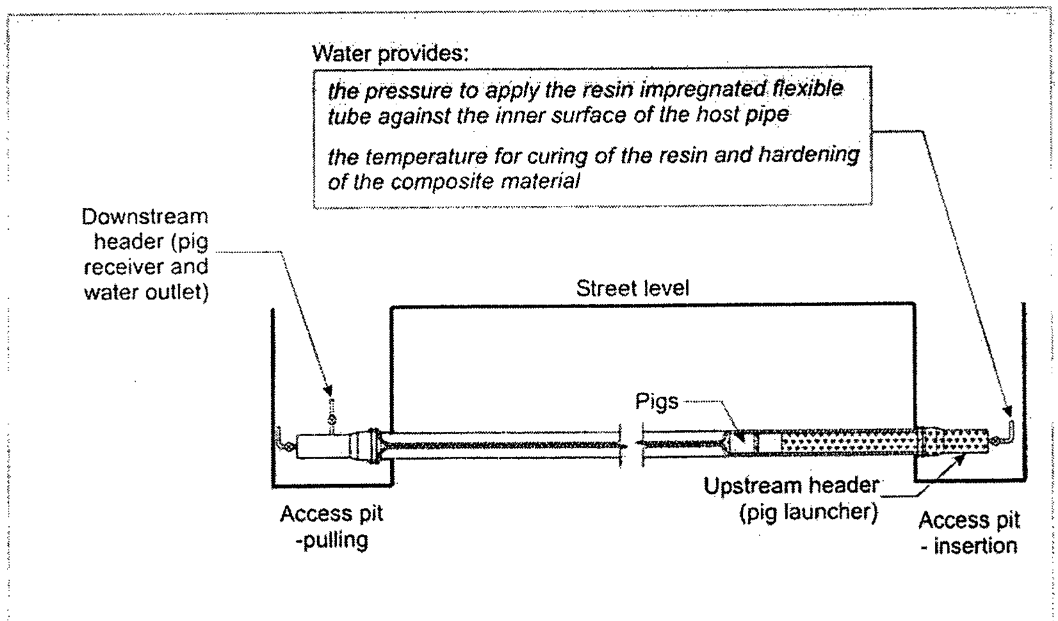
Folded PVC liner for watermain renovation, showing close fit after reversion

Appendix A

Insertion of a CIPP liner in a watermain

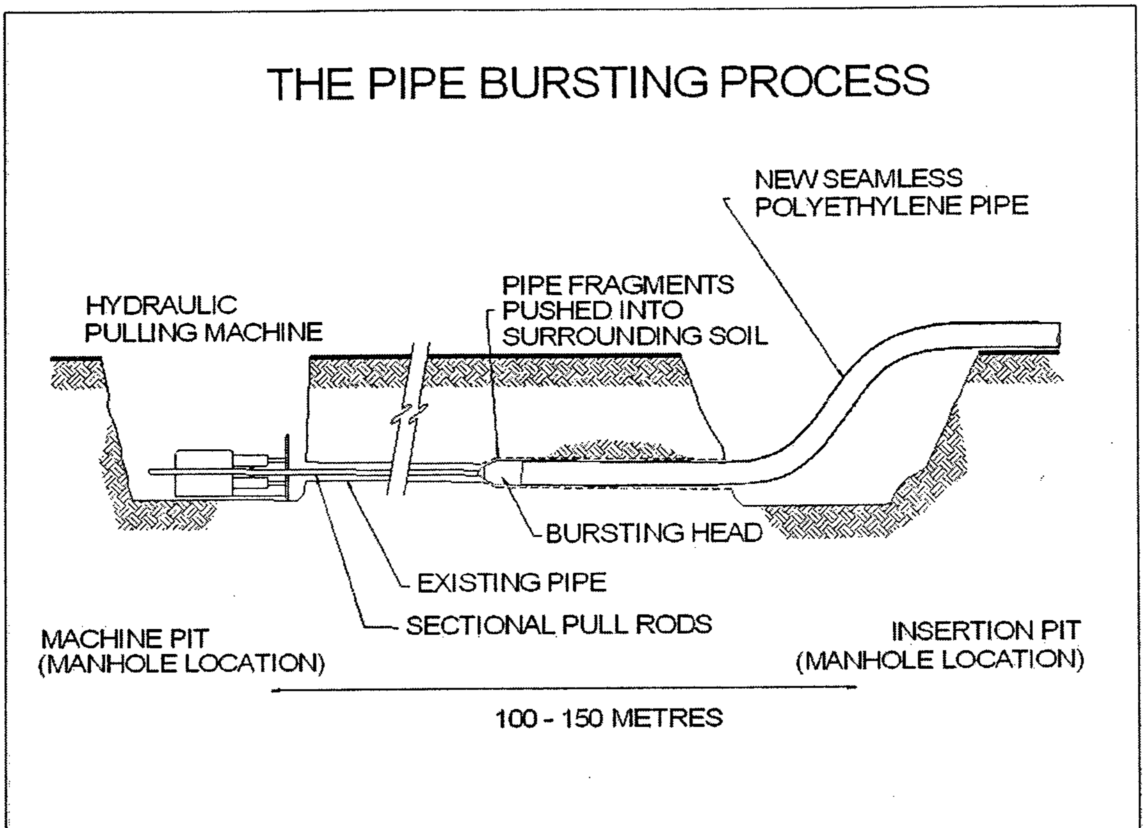


Forming and curing of CIPP liner



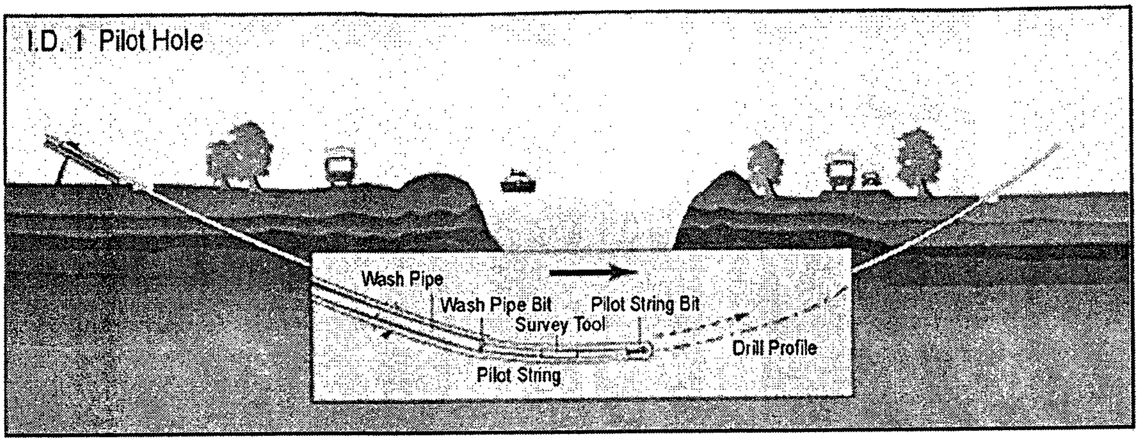
Source : Sanexen Environmental Services inc.

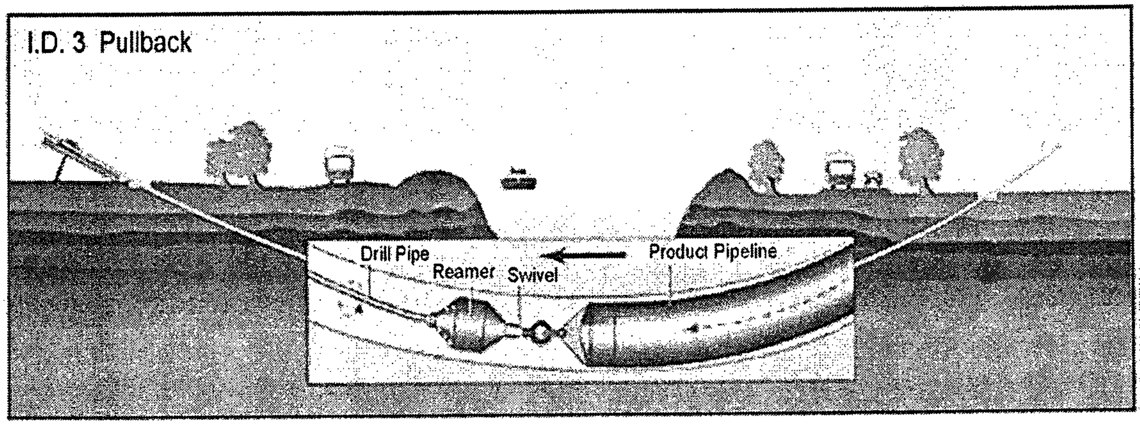
Appendix A



Courtesy of City of Nanaimo, British Columbia

Appendix A


I.D. 1 Pilot Hole
Wash Pipe
Wash Pipe Bit
Pilot String Bit
Survey Tool
Drill Profile
Pilot String


I.D. 3 Pullback
Drill Pipe
Reamer
Swivel
Product Pipeline

Appendix A-7: Limitations of the Trenchless Technology Techniques (National guide2003).

Technology	Diameter Range (mm)	Maximum Installation Range (m)	Rehabilitation Capability	Liner Material
Sliplining				
- Continuous	100 to 1600	300	**Full structural**	PE, PVC, PP, PE/EPDM
- Discrete sections	300 to 4000	1700	**Full structural**	PE, PVC, PP, GRP, DI
Close-fit sliplining	100 to 1000	100	Full and semi structural	PE, PP
- Diameter reduction	100 to 600	600		PE, PVC, FRP
- Site folded				
Cure-in-place				
- Felt based	100 to 2750	1000	Full and semi structural	Non-woven polyester fibre
- Woven Hose	100 to 1016	1000		Woven polyester fibre
- Membrane	100 to 2750	1000	Non-structural	Elastomeric membrane (note that all of the above include resin impregnation)
Pipe bursting	50 to 1200	150	**Full structural**	PE

Appendix A

Horizontal drilling	100 to 1200	600	**Full structural**	PE, PVC, DI, steel
Micro-tunnelling	300 or larger	200	**Full structural**	Concrete, DI, PE, PVC
Internal joint seals	400 or greater	No limit	**Full structural**	EPDM(structural at a joing seal location only)
Cement mortar lining	100 to 4500	500	Non-structural	Cement mortar
Epoxy lining	100 to 4500	500	Non-structural	Epoxy, Polyurea

Appendix A

Appendix 9: The advantages and drawbacks of utilizing Trenchless Technologies Techniques (National guide2003).

Technology	Advantages	Drawbacks
SLIPLINING	• Sliplining can be applied to most types of pipe. • It has an independent structural integrity and is not reliant on the integrity of the host pipe. • It is rapid and causes little disturbance to other utilities (when grouted, it is generally slower than other rehabilitation technologies). • It is an efficient technique to consider when there are long runs with few connections. • Usually, this method provides a better friction coefficient for improved hydraulic performance compared to the host pipe prior to rehabilitation.	• The sliplined pipe should be sized so its outside diameter is at least 10 percent smaller than the inside diameter to allow for smooth insertion. This reduction, in association with the wall thickness of the pipe, will cause a loss of cross-sectional capacity and can impact on hydraulic capacity. • When short pipe sections are used, there is an increased cost for joining pipes. • Poorly controlled grouting to the annular space can lead to the liner pipe buckling. • Multiple excavations may be required if many service and branch reconnections are involved. • The liners used for sliplining generally do not turn well through bend fittings. In most practical applications, all bend fittings must be excavated. As such, the geometry of the unlined pipe must be considered before selecting this technique.

CLOSE FIT SLIPLINING: DIAMETER REDUCTION	• Close fit diameter reduction sliplining can be applied to most types of pipe. • It is rapid and causes little disturbance to other utilities. • It is a useful technique when there are long runs with few connections. • It usually provides a better friction coefficient for improved hydraulic performance. • There is minimal loss of pipe diameter and no grouting compared to the traditional sliplining technique. • The liner can provide either full structural integrity or semi-structural integrity, depending on the condition and sizing of the host pipe.	• The energy required to reduce the pipe diameter increases dramatically with larger pipe sizes and greater wall thicknesses. • The tube being installed may get hung up in pipes that are deformed, have dimensional irregularities, or displaced joints. • Manufactured pipe for insertion usually requires special extrusion dies due to non-standard pipe diameters. • Sufficient site space is required to accommodate butt-fusion welding of pipes before the diameter reduction and during insertion. • As with standard sliplining, the geometry of the host pipe must be considered, as the winched pipe generally does not turn well through bent fittings. • The site-folded technique is less sensitive to the variations in diameter or pipe with dimensional irregularities, compared to the diameter reduction technique. • The liner may move in relation to the host pipe due to the type of material used and inherent stresses that

Appendix A

		may be locked into the liner. (Proper design may alleviate this concern.)
CURED-IN-PLACE PIPE	• Installation is relatively fast with minimal excavation. • Access to the water main is gained from an existing access hole. • The system can accommodate a variety of diameters and can negotiate bends. • Service connections can be reinstated by robotic cutters, reducing excavation requirements. • An improved interior friction coefficient increases hydraulic capabilities, even with the slight loss in cross-sectional area • It can be used in structural, semi-structural, and non-structural applications.	• As the diameter increases, the difficulty of installation increases. • The host pipe needs extensive up front investigation and planning to determine locations of appurtenances prior to cleaning and preparation. • The liner is flexible and requires support from the surrounding material before curing. • Under and over cuts at service connections may occur occasionally. • The weight of the liner may cause partial buckling and ovality during installation (usually associated with the inversion process).
PIPE BURSTING	• Cleaning the existing pipe is not necessary. • A larger diameter pipe can be inserted. This, in conjunction with the improved interior friction coefficient, can substantially increase the hydraulic capabilities of the	• Pit excavations are normally required to accommodate replacement pipe sections. • All water main appurtenances must be excavated before bursting and then reconnected to the new water main.

	new water main. • The process provides for full structural rehabilitation. • It is most successful when there are long runs with few connections.	• All underground structures within one meter of the existing water main to be rehabilitated may have to be excavated to avoid damage that may occur due to the force being transmitted, and the displacement of soil, by the bursting technique. • Surface or roadway may be susceptible to heaving or slumping. • Potential scoring damage to outside of new pipe wall may impact new water main material. • There is limited quality control of pipe bedding and sidefill support
HORIZONTAL DRILLING	• There is reduced disruption to surface operations, such as major thoroughfares, railway tracks, rivers, buildings, and trees. • Disruption of buried infrastructure is reduced compared to the open-cut method. • The method allows for a new water main alignment. • Usually, there are lower restoration costs than with the open-cut method.	• Larger working areas are normally required compared to other trenchless technologies, to accommodate drilling equipment and pipe material. • Exact pipe alignment can be difficult to attain, although the method is still fairly accurate. • The length of the pipe being installed is limited by the diameter of the pipe (the larger the diameter, the shorter the possible span). • Consistent soil conditions are normally required for good performance. • There is limited quality control of pipe bedding and

		side fill support.
INTERNAL JOINT SEALS	• This technology is specific to pipe joint issues only. • Minimal working space is required at the surface. • It is a low-cost alternative.	• It can only be used in pipe sizes suitable for worker access (i.e., 600 mm diameter or larger). • The technique does not address other possible pipe line deficiencies.

Appendix B

Comparison between Non-Destructive Evaluation Methods for Water Mains

Technical	**Thermography**	**Acoustic leak finder**	**Ultrasound**	**MFL**	**RFEC**
Pipe accessibility	No	No	Yes	Yes	Yes
Type of structural	Leak and break		Crack and corrosion pit		
Pipe type	PVC, CI, DI, PCRC	CI and DI	CI, DI, and PCRC		
Pipe diameter	Any	Any	>300mm	> 450mm	
Tuberculation	Any	<20%	< 10%	< 20%	
Weather condition effect	Dry and Moderate	Any			
Stray currents effect	Any	Affect readings			
Soil conditions effects	Clay soil N/A	Any			
Reading accuracy	0.5 -3m	0.5m to 1.0m	5mm	5mm	>3000mm2
Contractual					
By-pass requirements	No	No	Yes		
Locality of inspectors	According to budget and provision of contract				
Years in business	According to provision of contract				
Day time constrains	Any	Day time			
Inspection rate (Schedule constrain)	200 m/ hr	35m/hr	20m/hr	10m/hr	10m/hr
Cost Effectiveness					
Capital costs of the	The less expensive ranked from left to right				

- The average cost of the method depend on the size of the project and locality of the inspector
- Inspection rate depend on the model of the device and inspector experience

Appendix B

Example for average cost breakdown to compare two leak detection methods such as acoustic based leak finder and Thermography

Acoustic leak finder

Rent 300-450$/ day for 7 working hrs= 40-65$/hr

2 technicians x 30-40$/hr=60-80$/hr

Equipped van x 500-700 $/day= 70-100$/hr

Rate of inspection 20-35m/hr

Cost for inspection of 1 m using acoustic-based method = 7$

Thermography would cost the same in terms of equipments and technicians, but it provides high inspection rate

Average rate of inspection using thermography system = 200m/hr

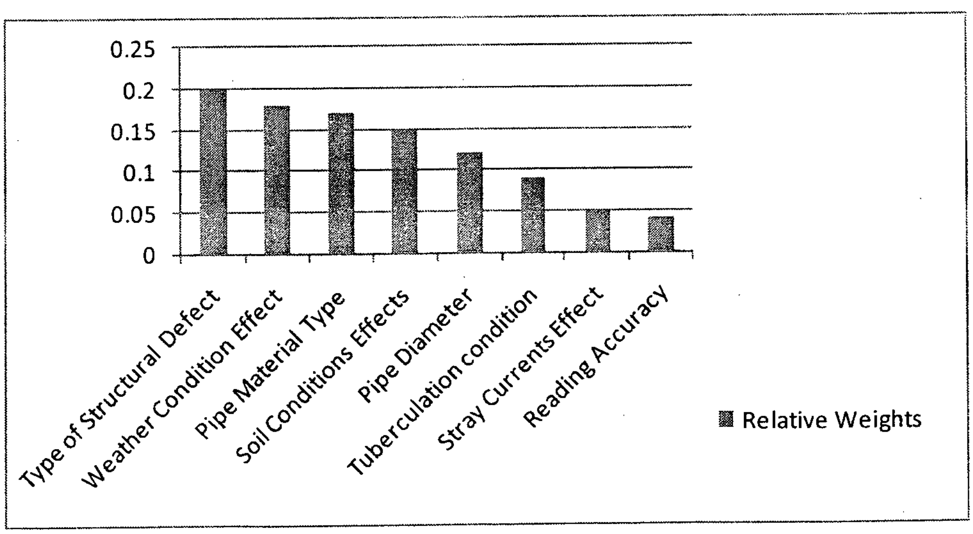
Cost for inspection of 1m using Thermography (IR Cmera) = 1.25$

Appendix B

Relative Weights for Technical Factors

	Ref.1	Ref.2	Ref.3	Ref.4	Ref.5
Type of Structural Defect	0.19	0.2	0.23	0.18	0.25
Weather Condition Effect	0.19	0.22	0.16	0.2	0.16
Pipe Material Type	0.18	0.15	0.17	0.18	0.14
Soil Conditions Effects	0.14	0.12	0.14	0.17	0.15
Pipe Diameter	0.14	0.1	0.11	0.1	0.17
Tuberculation condition	0.07	0.07	0.07	0.1	0.07
Stray Currents Effect	0.05	0.08	0.09	0.02	0.03

	Ref.6	Ref.7	Ref.8	Ref. 9	Ref.10
Type of Structural Defect	0.24	0.18	0.21	0.19	0.17
Weather Condition Effect	0.15	0.19	0.18	0.18	0.19
Pipe Material Type	0.16	0.18	0.17	0.16	0.2
Soil Conditions Effects	0.18	0.12	0.15	0.16	0.17
Pipe Diameter	0.12	0.12	0.12	0.14	0.12
Tuberculation condition	0.08	0.12	0.11	0.11	0.07
Stray Currents Effect	0.04	0.06	0.03	0.03	0.04



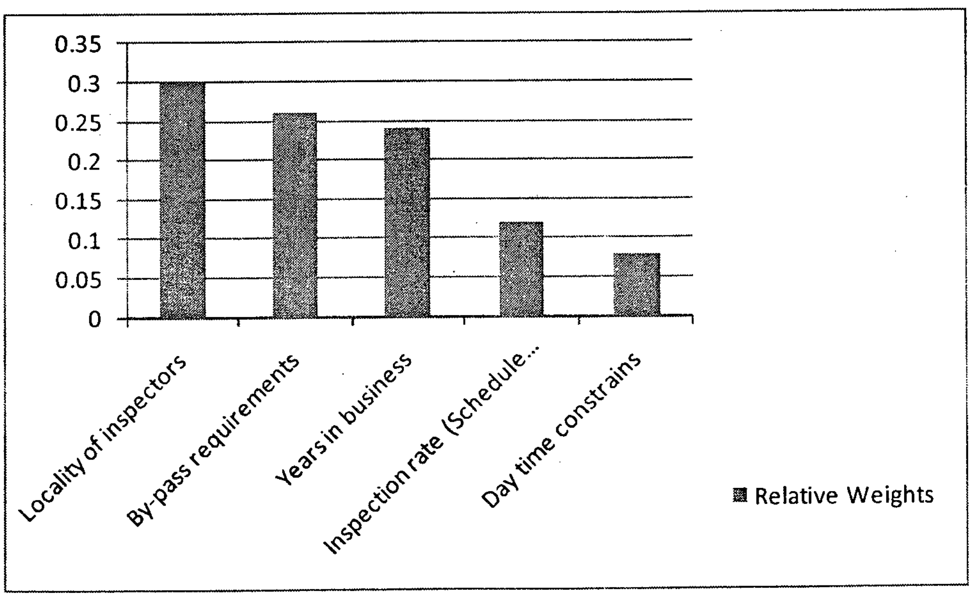
Average Weights for Technical Factors

Appendix B

Relative Weights for Contractual Factors

	Ref.1	Ref.2	Ref.3	Ref.4	Ref.5
Locality of inspectors	0.32	0.3	0.32	0.27	0.31
By-pass requirements	0.25	0.28	0.22	0.28	0.24
Years in business	0.23	0.21	0.25	0.25	0.28
Inspection rate	0.14	0.12	0.12	0.1	0.09
Day time constrains	0.06	0.09	0.09	0.1	0.08

	Ref.6	Ref.7	Ref.8	Ref. 9	Ref.10
Locality of inspectors	0.28	0.33	0.28	0.27	0.32
By-pass requirements	0.23	0.28	0.29	0.25	0.28
Years in business	0.22	0.21	0.23	0.28	0.22
Inspection rate	0.15	0.1	0.12	0.14	0.11
Day time constrains	0.12	0.08	0.08	0.06	0.07



Average Weights for Technical Factors

Appendix B

Calculation of Consistency Ratio (Saaty 1982)

CR= CI/ Random consistency

Where:

CI: Consistency Index = $\lambda_{max} - N/(N-1)$

λ_{max}: Eigen value of the matrix containing weights

N: Number of considered attributes

Random consistency: a number is function in number of attributes (size of matrix) as shown in Table below

Size of Matrix (Number of Attributes)	Random Value
1	0
2	0
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49

Appendix C

Data Used for α Calculation

Exp.#	α/2	α	Depth (m)	Average Virtual Diameter (m)	Pipe Length (m)
1	40.2	80.4	1.8	3.04	48.7
2	42.9	85.8	2.1	3.9	146
3	45.1	90.2	1.9	3.8	300
4	45.5	91	2.20	4.5	56
5	45.5	91	2.2	3.8	80
6	46.1	92.2	1.85	3.85	133
7	46.4	92.8	1.95	3.8	218
8	46.5	93	1.9	4	122
9	46.78	93.56	1.95	4.15	176
10	47.2	94.4	2.1	4.55	265
11	47.5	95	2.15	4.7	180
12	48	96	1.9	4.2	217
13	50.1	100.2	1.8	4.3	93
14	51.7	103.4	1.9	4.8	148
15	51.8	103.6	1.8	4.6	187
16	52.2	104.4	1.85	4.8	291
17	52.5	105	1.8	4.7	249
18	52.7	105.4	1.85	4.85	170
19	53	106	1.85	4.9	186
20	53.4	106.8	2.1	5.65	69
21	53.6	107.2	1.85	5	228
22	55	110	1.9	5.4	192
23	58.2	116.4	1.8	5.8	246
24	60.4	120.8	1.85	6.5	218
25	61.7	123.4	1.8	6.75	289

Best subset

Vars	R2	R2 adj	Mallows Cp	S
Av.Dim	87.2	86.7	71.4	3.9
Depth	40.3	37.7	411.5	8.4
Both	97	96.7	3	1.9

$\alpha^{\circ} = 100 - 25.2$ Depth (m) + 10.5 Average Virtual Diameter (m)

R-Sq = 97.0%   R-Sq(adj) = 96.7%

Appendix C

Predictor	Coef	SE Coef	T	P
Constant	100.14	7.10	14.10	0.00
Depth (m)	-25.2	3.00	-8.39	0.00
Average Virtual Diameter (m)	10.5	0.52	20.26	0.00

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	2	2616.2	1308.1	351.22	0.00
Residual Error	22	81.9	3.7		
Total	24	2698.1			

Obs	Depth (m)	αo	Fit	SE Fit	Residual	St Resid
1	2.20	80.400	83.552	0.846	-3.152	-1.82
2	2.10	85.800	88.171	0.629	-2.371	-1.30
3	1.90	90.200	92.160	0.644	-1.960	-1.08
4	2.20	91.000	91.950	0.840	-0.950	-0.55
5	2.20	91.000	84.602	0.834	6.398	3.68R
6	1.85	92.200	93.945	0.705	-1.745	-0.97
7	1.95	92.800	90.901	0.590	1.899	1.03
8	1.90	93.000	94.260	0.567	-1.260	-0.68
9	1.95	93.560	94.575	0.469	-1.015	-0.54
10	2.10	94.400	94.994	0.596	-0.594	-0.32
11	2.15	95.000	95.309	0.738	-0.309	-0.17
12	1.90	96.000	96.359	0.499	-0.359	-0.19
13	1.80	100.200	99.928	0.656	0.272	0.15
14	1.90	103.400	102.657	0.404	0.743	0.39
15	1.80	103.600	103.077	0.587	0.523	0.28
16	1.85	104.400	103.917	0.465	0.483	0.26
17	1.80	105.000	104.127	0.572	0.873	0.47
18	1.85	105.400	104.442	0.464	0.958	0.51
19	1.85	106.000	104.967	0.464	1.033	0.55
20	2.10	106.800	106.540	0.897	0.260	0.15
21	1.85	107.200	106.016	0.468	1.184	0.63
22	1.90	110.000	108.955	0.520	1.045	0.56
23	1.80	116.400	115.673	0.697	0.727	0.40
24	1.85	120.800	121.761	0.961	-0.961	-0.57
25	1.80	123.400	125.121	1.048	-1.721	-1.06

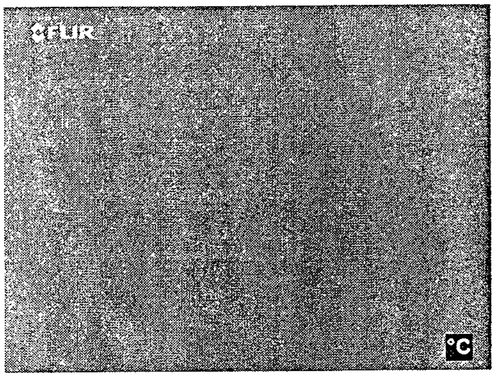
R denotes an observation with a large standardized residual.

Appendix C

Sample of Daily Weather Condition for April 2007

Daily Data Report for April 2007											
Day	Max Temp °C	Min Temp °C	Mean Temp °C	Heat Deg Days °C	Cool Deg Days °C	Total Rain mm	Total Snow cm	Total Precip mm	Snow on Grnd cm	Dir of Max Gust 10's Deg	Spd of Max Gust km/h
1	13.5	-2.4	5.6	12.4	0	0.8	T	0.8	0		
2	8.8	4.3	6.6	11.4	0	9	0	9	0		
3	9.6	4.5	7.1	10.9	0	0.6	0	0.6	0		
4	4.6	0.2	2.4	15.6	0	23.1	6.7	30.2	0		
5	2.7	-1.8	0.5	17.5	0	1.4	2.8	4.8	5		
6	-0.1	-4.1	-2.1	20.1	0	0	0.2	0.2	0		
7	0.4	-5.2	-2.4	20.4	0	0	0.6	0.6	1		
8	1.1	-4.7	-1.8	19.8	0	0	0.2	0.2	T		
9	5.1	-1.3	1.9	16.1	0	T	T	T	0		
10	6.1	-2.6	1.8	16.2	0	0	0	0	0		
11	5.6	-4.1	0.8	17.2	0	0	0	0	0		
12	4.5	0.3	2.4	15.6	0	2.8	14	19.4	0		
13	3.2	0.4	1.8	16.2	0	0.4	0.6	1	5		
14	7	1.7	4.4	13.6	0	T	0	T	1		
15	5.1	0.1	2.6	15.4	0	8.4	22	30.4	0		
16	4.3	0.4	2.4	15.6	0	3.6	9.4	16.4	8		
17	5.6	0.7	3.2	14.8	0	3.6	4.8	8.4	T		
18	12.4	3.3	7.9	10.1	0	0.2	0	0.2	0		
19	16.6	2.5	9.6	8.4	0	0	0	0	0		
20	20.6	2.3	11.5	6.5	0	0	0	0	0		
21	21.2	3	12.1	5.9	0	0	0	0	0		
22	22.7	5.7	14.2	3.8	0	0	0	0	0		
23	25.8	8.6	17.2	0.8	0	1.2	0	1.2	0		
24	14.9	3.9	9.4	8.6	0	0	0	0	0		
25	12.9	4	8.5	9.5	0	0	0	0	0		
26	15	1.9	8.5	9.5	0	T	0	T	0		
27	12.7	8.8	10.8	7.2	0	8.2	0	8.2	0		
28	9.8	7.2	8.5	9.5	0	5	0	5	0		
29	11.5	5.7	8.6	9.4	0	2.4	0	2.4	0		
30	14.5	4.7	9.6	8.4	0	0.6	0	0.6	0		
Sum				366.4	0	71.3	61.3	139.6			
Avg	9.9	1.6	5.8								
Xtrm	25.8	-5.2									

Appendix C



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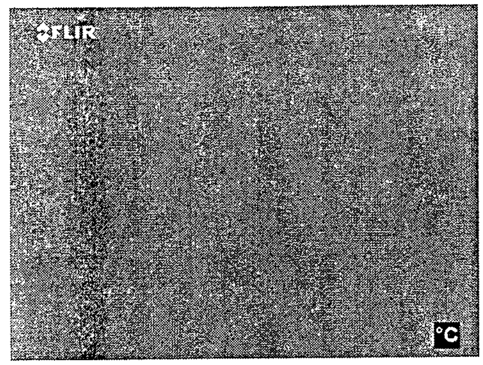

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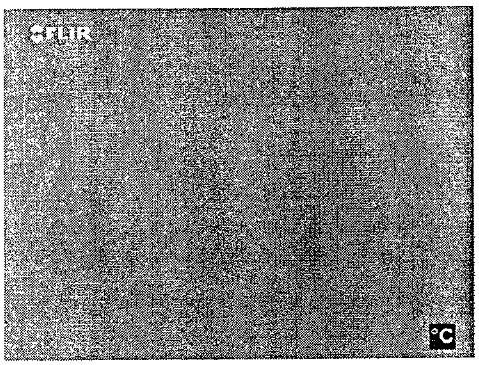

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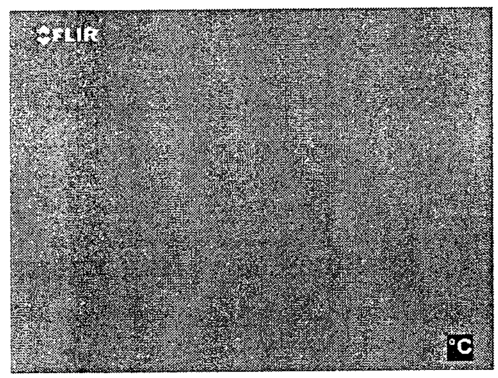

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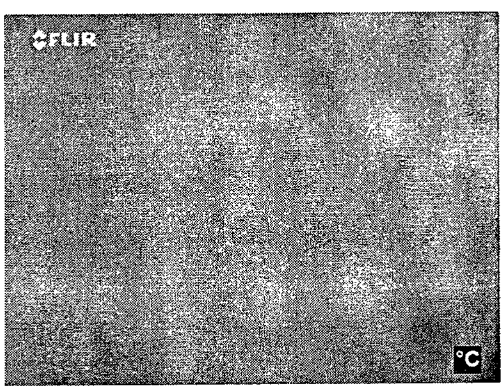

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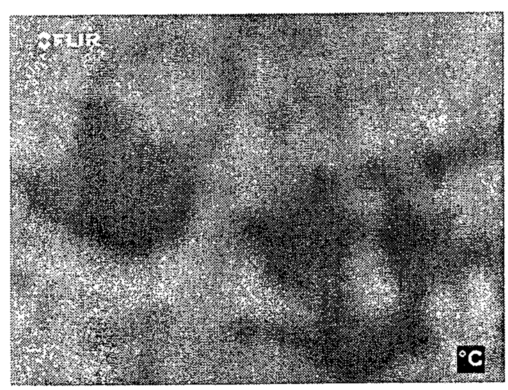


IR_ 6

Sequential Images Captured for Pipeline Indicating Thermal Contrast Due to Leak at Image # 6

Appendix C

Sample of the Difference in Soil Temperature in Four Seasons

Winter

Z (m)	Temp.° C
0	-6
1	2
1.8	4

Spring

Z (m)	Temp.° C
0	4
1	6
1.8	9

Summer

Z (m)	Temp.° C
0	28
1	20
1.8	14

Fall

Z (m)	Temp.° C
0	12
1	8
1.8	5

Appendix D

Sample of Raw Data

Location	ID	Pipe age	Pipe Diameter	Wall thick	corrosion depth	t	Pit / Spun	Bursting tensile strength	Ring rupture modulus	Fracture toughness	Soil acidity/alkalinity	Soil Resis.	Soil areation
			D	t	d	t_{rem}		S	R	Kq	pH	ρ_{soil}	
		yr	in	in	in	in		psi	psi	psi√in			
Boston	BS-1-B-9	110.0	6.0	0.5	0.1	0.4	1.0	18603.5	39150.0	8361.1	6.2	1920.0	good
Boston	BS-2-B-10(1)	102.0	6.0	0.5	0.0	0.5	1.0	21197.6	39150.0	7842.5	7.6	2294.0	good
Chicago	CH-1-A-7	86.0	8.0	0.6	0.1	0.5	1.0	15974.7	30450.0	7706.0	7.5	29000.0	good
Chicago	CH-3-12/5	107.0	6.0	0.5	0.2	0.3	1.0	15639.7	30450.0	8106.3	7.3	13000.0	fair
Denver	DN-5-2	51.0	6.0	0.4	0.0	0.4	2.0	41142.3	40600.0	13783.5	8.7	3589.0	poor
Denver	DN-5-3	51.0	6.0	0.4	0.0	0.4	2.0	43096.9	40600.0	13574.2	8.7	3589.0	poor
Edmonton	ED-1-B/A-6(1)	65.0	6.0	0.4	0.0	0.4	1.0	29899.0	36250.0	10535.5	7.7	539.0	very poor
Edmonton	ED-1-B/A-7(1)	65.0	6.0	0.5	0.0	0.5	1.0	30189.0	36250.0	12491.6	7.7	539.0	very poor
Minneapolis	MP-1-B-5	110.0	6.0	0.5	0.0	0.5	1.0	4799.5	36250.0	5195.0	7.9	1433.0	good
Minneapolis	MP-1-B-6	110.0	6.0	0.5	0.0	0.5	1.0	9831.0	36250.0	7160.1	7.9	1433.0	good
Moncton	MN-1-1(1)	38.0	6.0	0.4	0.0	0.4	2.0	43630.5	44050.0	12919.2	5.8	1477.0	good
Moncton	MN-1-2	38.0	6.0	0.4	0.0	0.4	2.0	43108.5	44050.0	13292.2	5.8	1477.0	good
Quebec City	QC-1-11/4	46.0	10.0	0.4	0.1	0.3	2.0	21503.5	44500.0	12555.2	7.0	1000.0	fair
Quebec City	OC-3-A-10	49.0	6.0	0.5	0.0	0.5	2.0	31276.5	44500.0	10462.7	8.0	8636.0	good
RMOC	OC-3-B-2	49.0	6.0	0.5	0.0	0.5	2.0	30493.5	44500.0	10317.1	8.0	8636.0	good
RMOC	OC-6-A-2/5.10	35.0	6.0	0.4	0.1	0.3	2.0	23171.0	44500.0	11090.5	7.9	681.0	fair
San Francisco	SF-1-7/4	51.0	8.0	0.4	0.1	0.4	2.0	20996.0	37700.0	12009.4	6.3	2675.0	good
San Francisco	SF-2-6	65.0	8.0	0.4	0.0	0.4	1.0	27148.4	31900.0	12218.6	5.9	1711.0	good
St. Louis	SL-1-7	51.0	6.0	0.4	0.0	0.4	2.0	39164.5	42000.0	10371.7	5.7	1680.0	fair
St. Louis	SL-2-8	49.0	6.0	0.4	0.0	0.4	2.0	40386.9	42000.0	9789.4	5.0	1540.0	good
Toronto	TO-1-8/2	108.0	6.0	0.5	0.1	0.4	1.0	25785.4	30450.0	10007.8	7.9	1000.0	good
Toronto	TO-2-9/3	66.0	6.0	0.5	0.0	0.4	1.0	32139.3	46400.0	11645.4	8.2	1200.0	good
Vancouver	VN-1-A-4	22.0	6.0	0.5	0.0	0.5	2.0	30174.5	31900.0	9707.6	5.5	7729.0	good
Vancouver	WN-2-A-5	40.0	6.0	0.4	0.0	0.4	2.0	27129.5	37700.0	12719.0	7.4	547.0	fair
Washington	WS-4-10	44.0	6.0	0.4	0.0	0.3	2.0	41644.0	43500.0	12409.7	5.1	6700.0	very poor
Washington	WN-1-A-2	22.0	6.0	0.4	0.0	0.4	2.0	22852.0	60900.0	10817.5	7.0	257.0	fair
Winnipeg	WN-3-A-4	37.0	6.0	0.4	0.0	0.4	2.0	28347.5	37700.0	11918.4	7.1	520.0	fair
Winnipeg	WN-3-B-1/10	37.0	6.0	0.4	0.0	0.4	2.0	27912.5	37700.0	9816.7	7.1	520.0	fair
Montreal	MO-1-1/2	85.0	6.0	0.4	0.0	0.4	1.0	15747.0	30450.0	8661.3	8.0	1200.0	good
Montreal	MO-1-2/2	66.0	8.0	0.5	0.0	0.4	1.0	32139.3	46400.0	11645.4	8.2	1200.0	good
Philadelphia	PH-2-3	35.0	8.0	0.4	0.0	0.4	2.0	37337.5	49300.0	12919.2	8.2	3691.0	very poor
Philadelphia	PH-2-6	51.0	6.0	0.4	0.0	0.4	2.0	41142.3	40600.0	13783.5	8.7	3589.0	poor

Appendix D

Sample of Raw Data

Material	Reference	Duration	Age (yr)	Tensile strength(MPa)	Modulus of rupture(MPa)
Pit	7C.1-1908 (AWWA 1908)	1908 to 1952	89-45	138	248
Pit	A21.1-39 (AWWA 1939)	1939 to 1967	58-30	76	207–214
Pit	Rajani et al. (2000)	pipe age: 64–115 yrs	115-64	33–267	132–379
Spun	C106-75 (AWWA 1975)	1953 to 1982	44-15	124	276
Spun	C106-75 (AWWA 1975)	1967 to 1982	30-15	145	310
Spun	Rajani et al. (2000)	pipe age: 22–51 yrs	51-22	135–305	194–445

Aeration Class	Aeration Constant (n)	Proportionality Constant, Kn mm/yr,Ω-cm	Redox Potential(mV)	Soil Type
Poor	0.5	9	50	high-low inorganic clay and silts and clayey sand
Fair	0.3333	5.64	150	high-low plastic organic clay and silty sand
Good	0.167	4.32	250	gravel, sand
Mixed	0.3	9.3	(-)166 to 365	mostly clay

pH	Classification
> 8.5	Strongly Alkaline
7.9-8.5	Moderately Alkaline
7.3-7.9	Slightly Alkaline
6.7-7.3	Neutral
6.2-6.7	Slightly acid
5.6-6.2	Moderately Acid
3.0-5.6	Strongly Acid

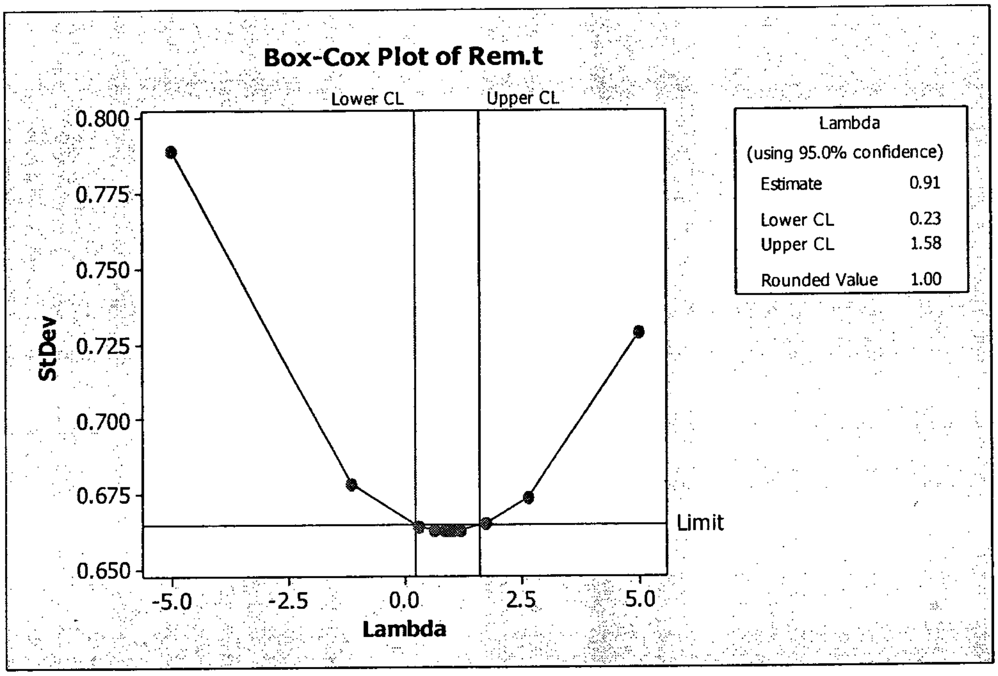
Appendix D

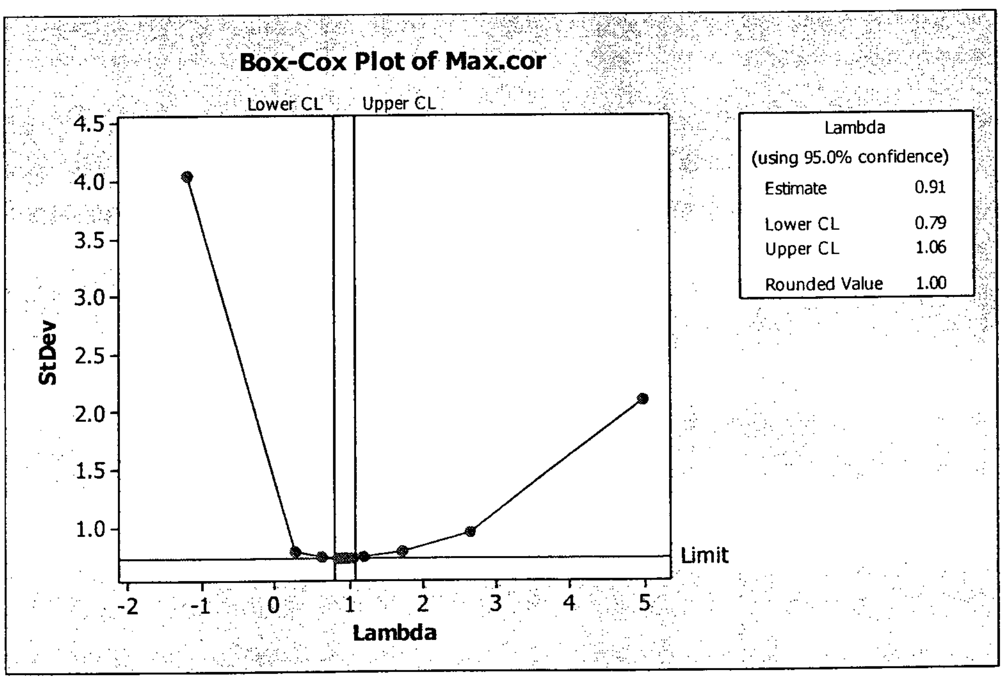
Sample of the Inputs/ Output Data (Remaining Useful Life of CI Water Mains)

Dim	Rem.t	Max.cor	age	S	R	pH	Resis.	Ar.index	W	SF	RUL
150.0	9.9	1.2	110.0	76.0	207.0	5.0	1001.0	9.0	20.8	2.0	3.7
200.0	9.9	1.3	110.0	76.0	269.0	8.0	1902.0	5.6	26.1	1.5	11.3
150.0	9.7	2.0	110.0	76.6	207.4	6.0	1201.0	9.0	20.8	1.5	15.4
150.0	8.3	1.4	107.0	77.1	207.8	7.0	11011.0	9.0	20.8	1.2	85.1
150.0	10.2	1.5	107.0	77.7	208.1	8.0	1502.0	4.3	20.8	2.0	1.6
150.0	10.7	2.4	102.0	78.2	208.5	4.5	2102.0	4.3	34.1	1.5	10.8
200.0	11.5	3.2	101.0	78.3	178.0	6.1	1570.0	4.3	22.4	1.2	68.8
150.0	11.5	2.4	101.0	78.3	178.0	6.1	1570.0	4.3	22.4	1.5	11.2
200.0	11.5	3.2	101.0	78.3	178.0	6.1	1570.0	4.3	22.4	1.2	68.8
150.0	11.5	1.0	101.0	78.3	178.0	6.1	1570.0	4.3	22.4	2.0	0.1
200.0	11.5	3.2	101.0	78.3	178.0	6.1	1570.0	4.3	22.4	1.2	68.8
150.0	11.5	2.4	101.0	78.3	178.0	6.1	1570.0	4.3	22.4	1.5	11.2
150.0	11.5	1.0	101.0	78.3	178.0	6.1	1570.0	4.3	22.4	2.0	0.1
150.0	10.4	1.1	102.0	79.3	209.3	6.0	551.0	9.0	34.1	2.0	2.0
150.0	10.9	2.7	102.0	79.9	209.7	6.5	3003.0	9.0	34.1	1.5	76.1
150.0	8.9	2.0	93.0	80.4	210.0	7.0	1201.0	9.0	18.2	1.2	19.1
150.0	11.2	2.4	93.0	81.0	210.4	8.0	4004.0	9.0	18.2	2.0	143.6
150.0	9.1	1.5	86.0	81.5	210.8	8.5	2002.0	9.0	18.2	1.5	38.2
150.0	9.9	1.1	86.0	81.5	210.8	4.8	12012.0	5.6	26.1	1.5	18.6
150.0	9.2	2.1	86.0	82.1	211.2	7.5	1802.0	9.0	29.7	1.2	39.0
150.0	11.7	2.6	86.0	82.1	213.6	6.0	2102.0	5.6	26.1	1.5	49.2
150.0	10.9	2.7	86.0	82.3	214.5	8.0	3003.0	4.3	26.1	1.2	91.1
150.0	11.4	2.8	86.0	82.6	211.6	7.0	3203.0	5.6	29.7	2.0	130.8
150.0	11.2	1.8	86.0	82.8	216.4	6.7	3003.0	4.3	43.0	1.5	5.7
150.0	9.9	1.4	86.0	83.0	217.3	8.1	6206.0	4.3	43.0	1.2	3.4
150.0	9.4	1.7	86.0	83.2	211.9	6.5	781.0	5.6	29.7	1.5	6.5
150.0	9.9	1.8	86.0	83.4	219.2	7.5	6006.0	9.0	22.4	1.5	99.6

Appendix D

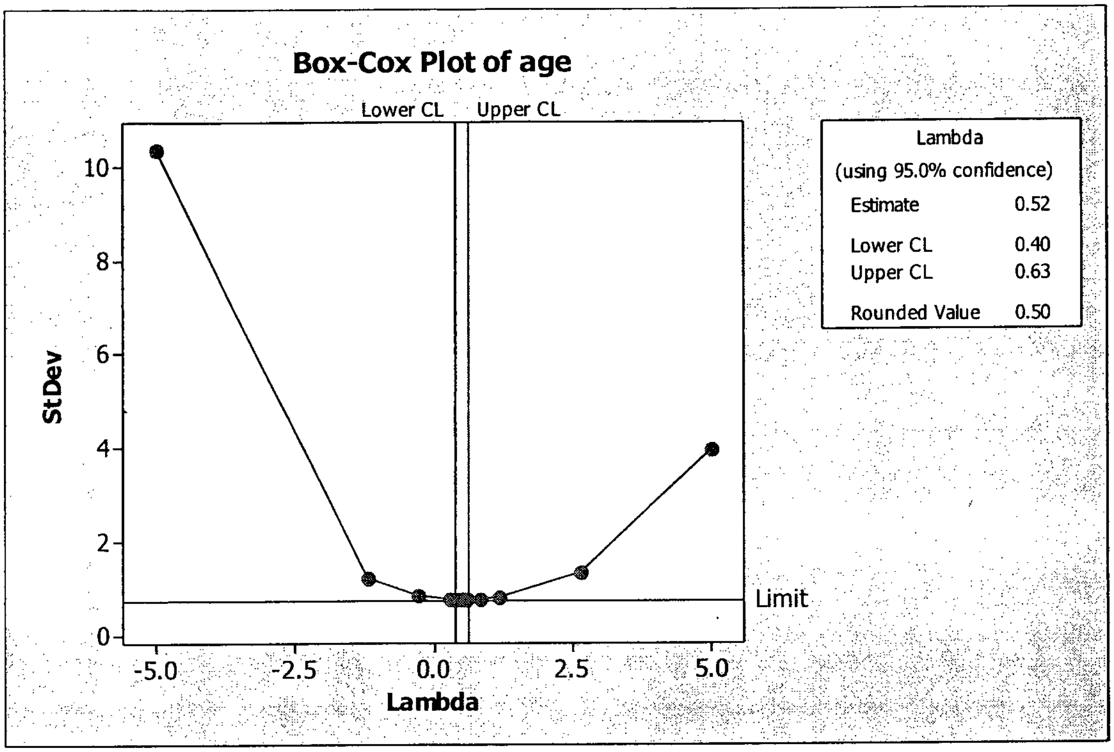
Box-Cox Power Transformation

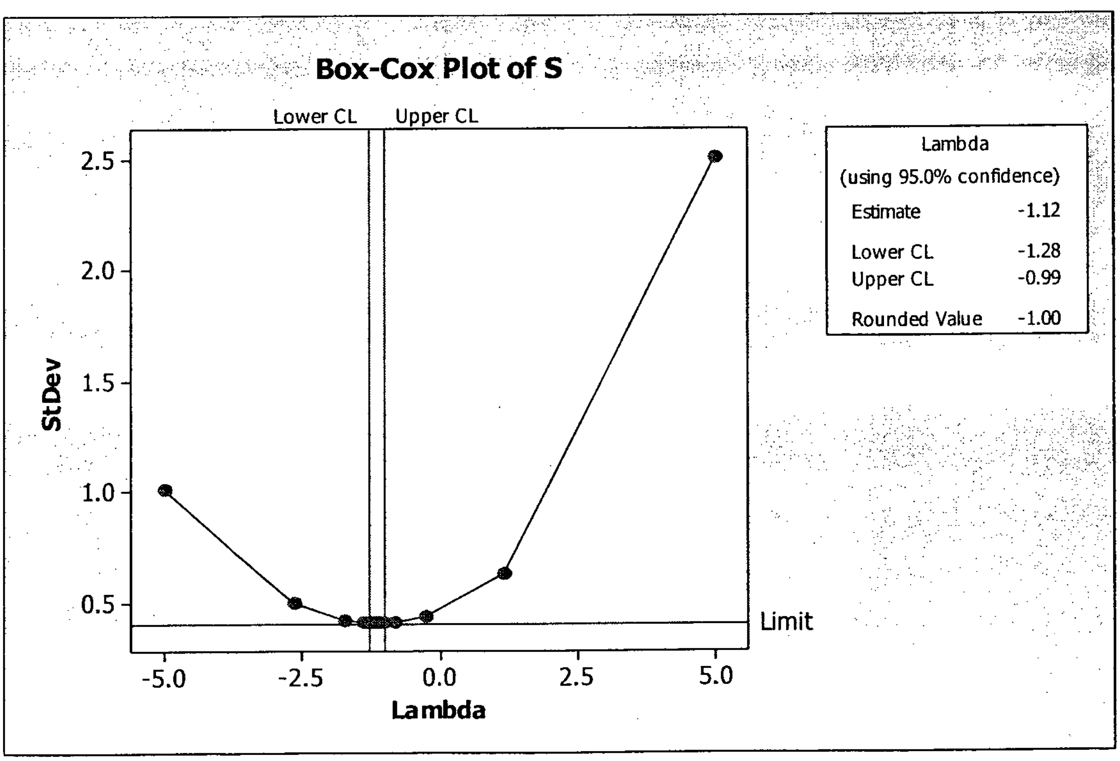




Appendix D

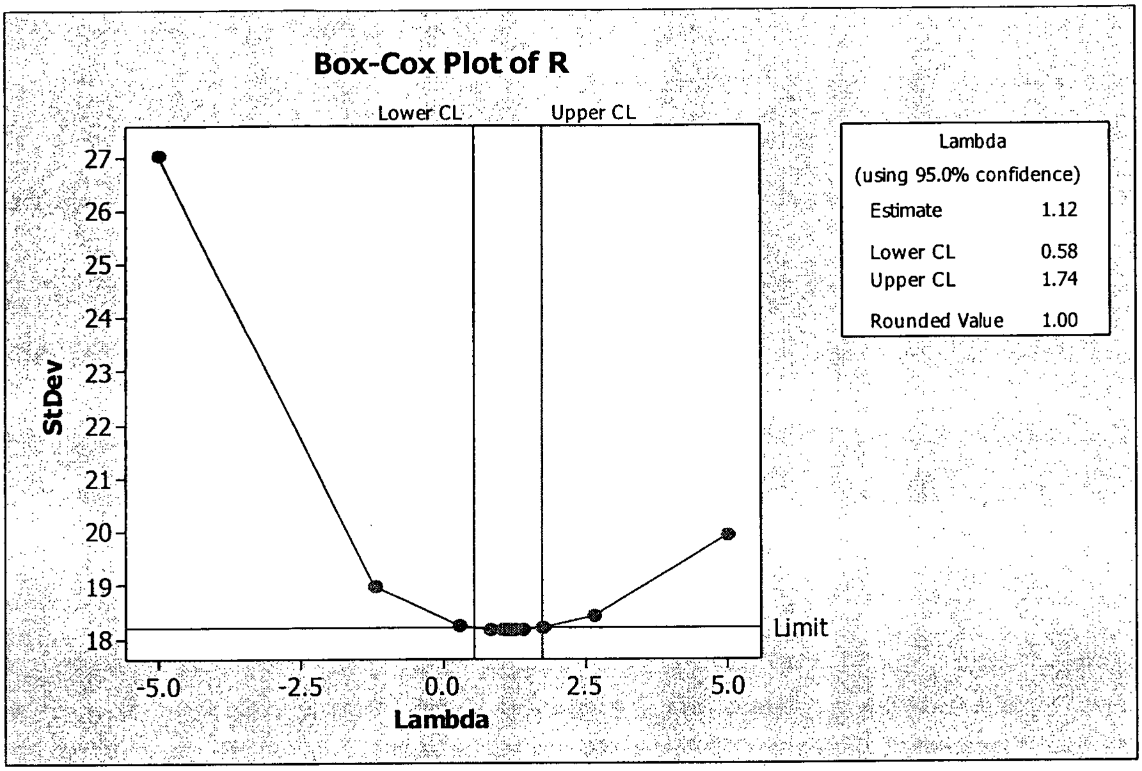
Box-Cox Power Transformation

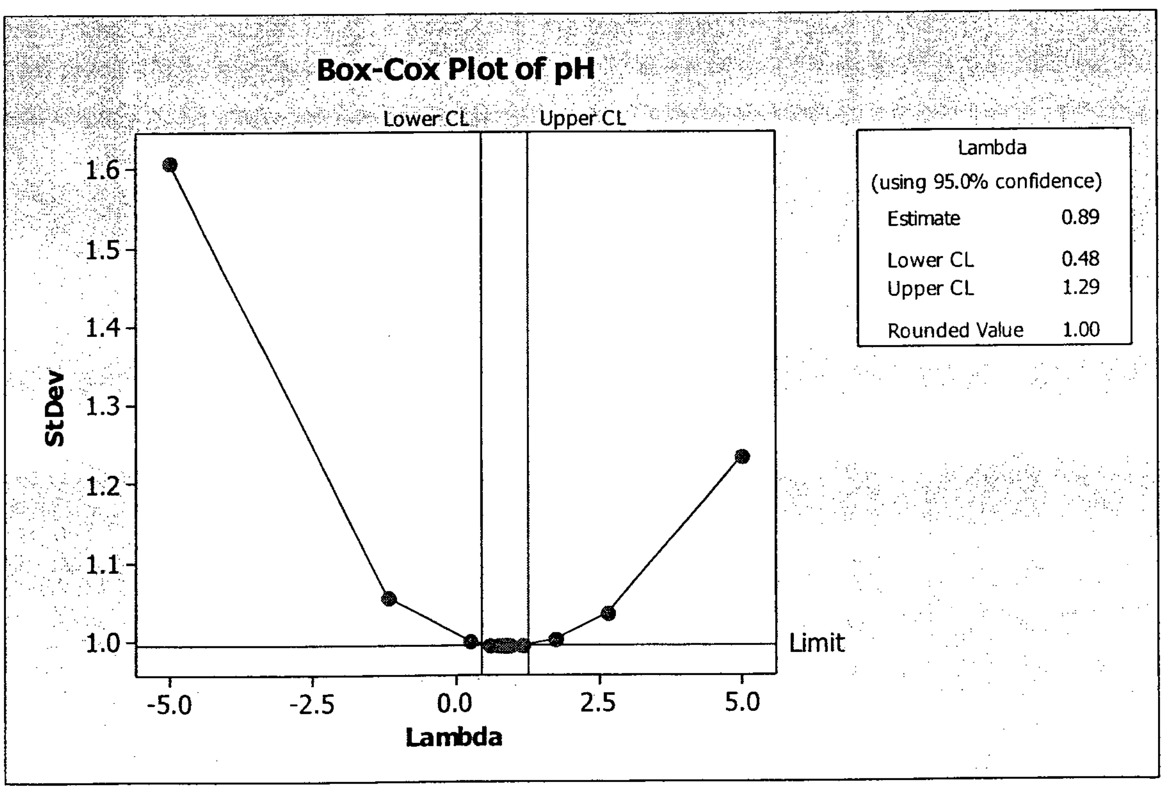




Appendix D

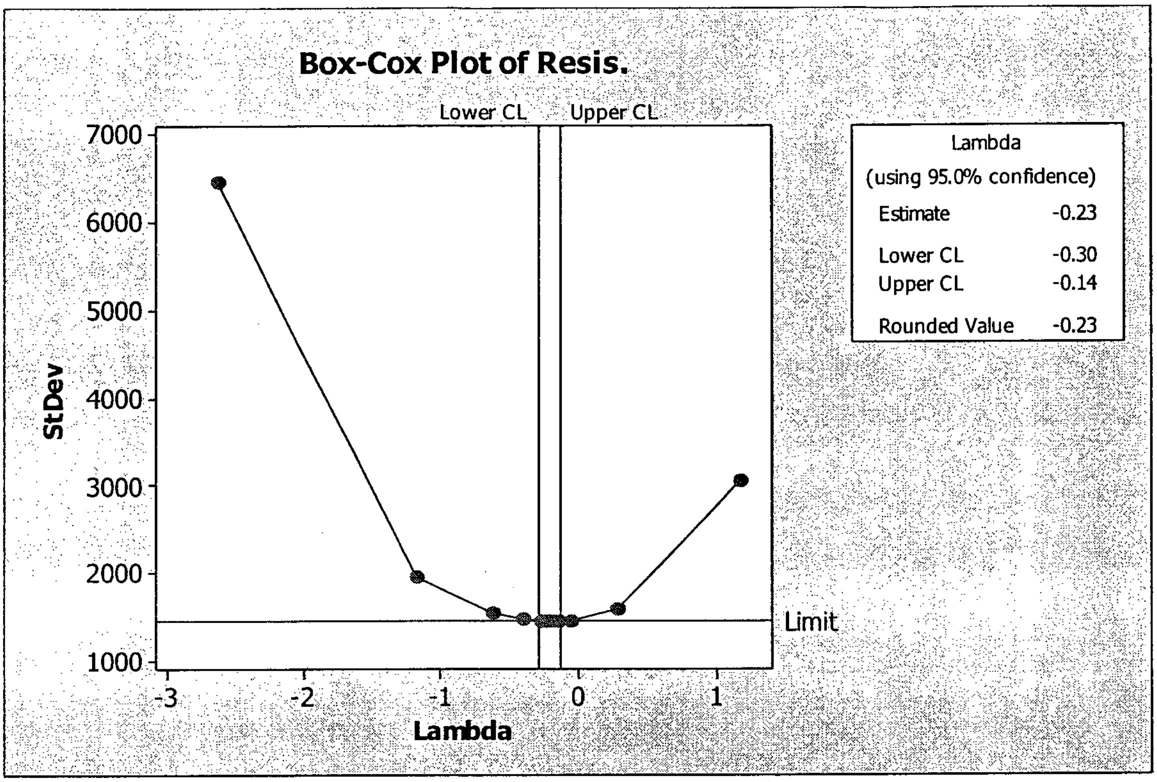
Box-Cox Power Transformation

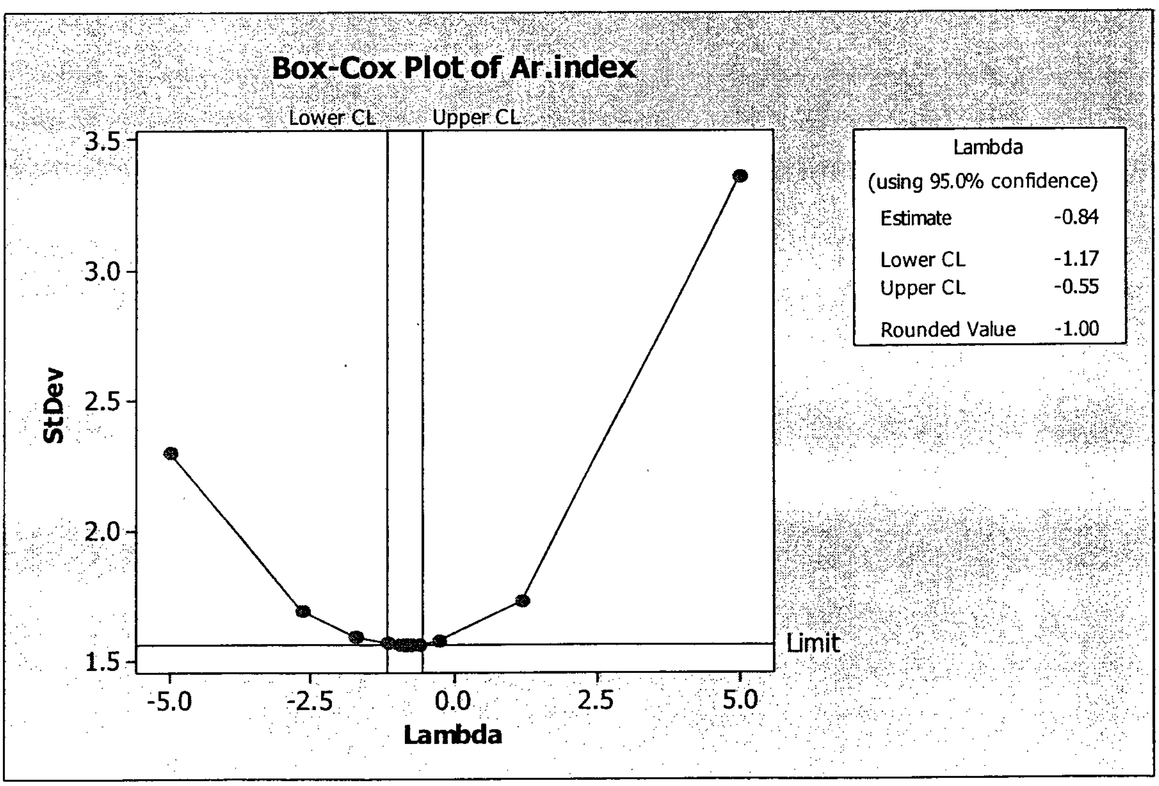




Appendix D

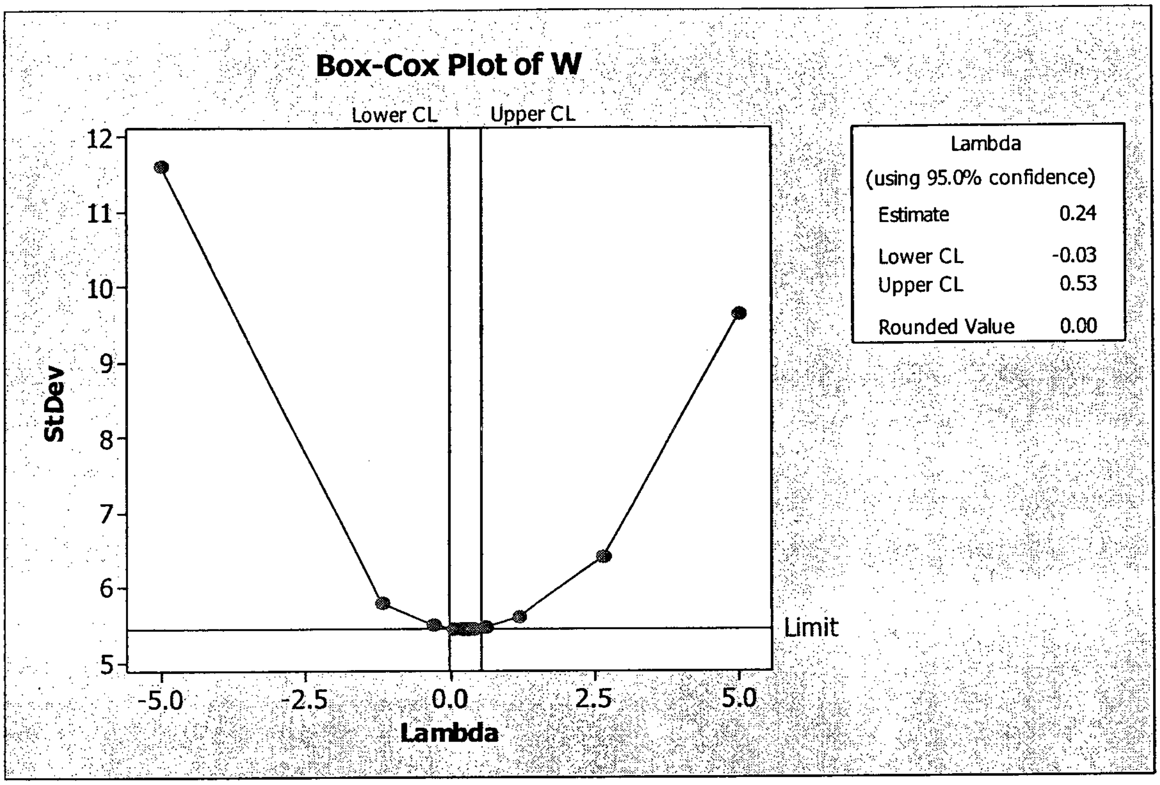
Box-Cox Power Transformation

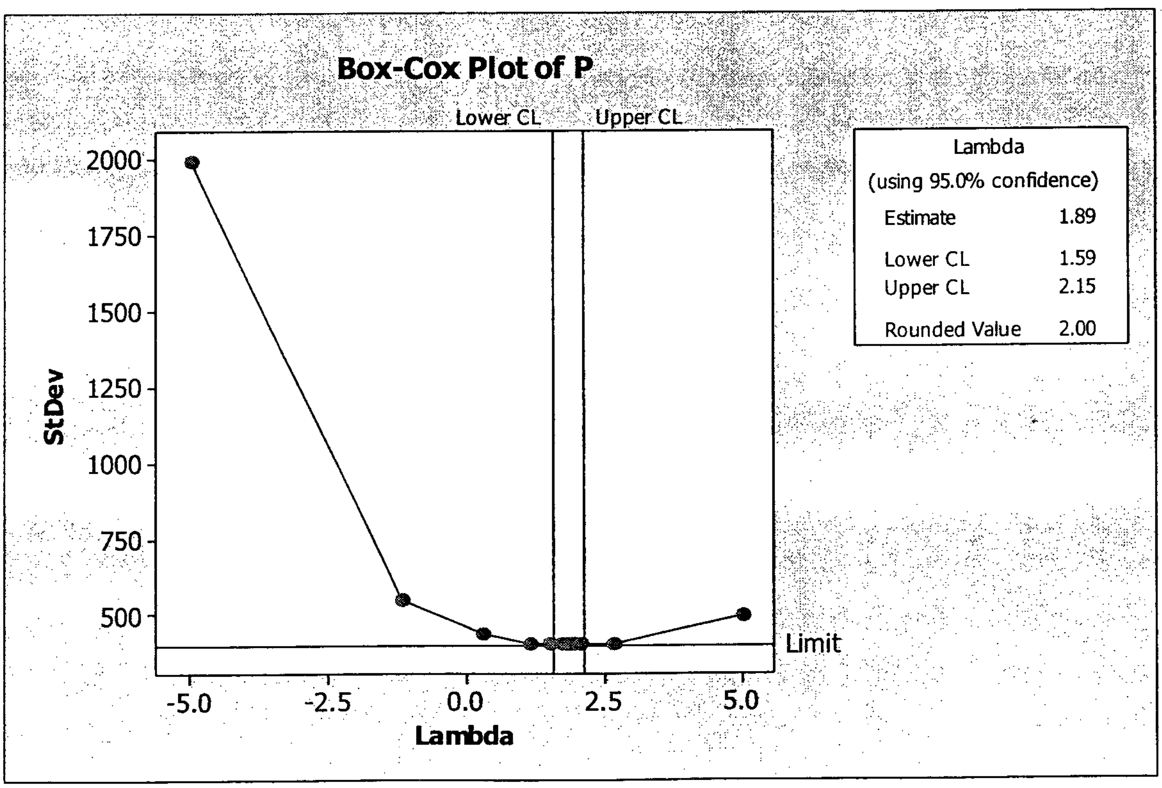




Appendix D

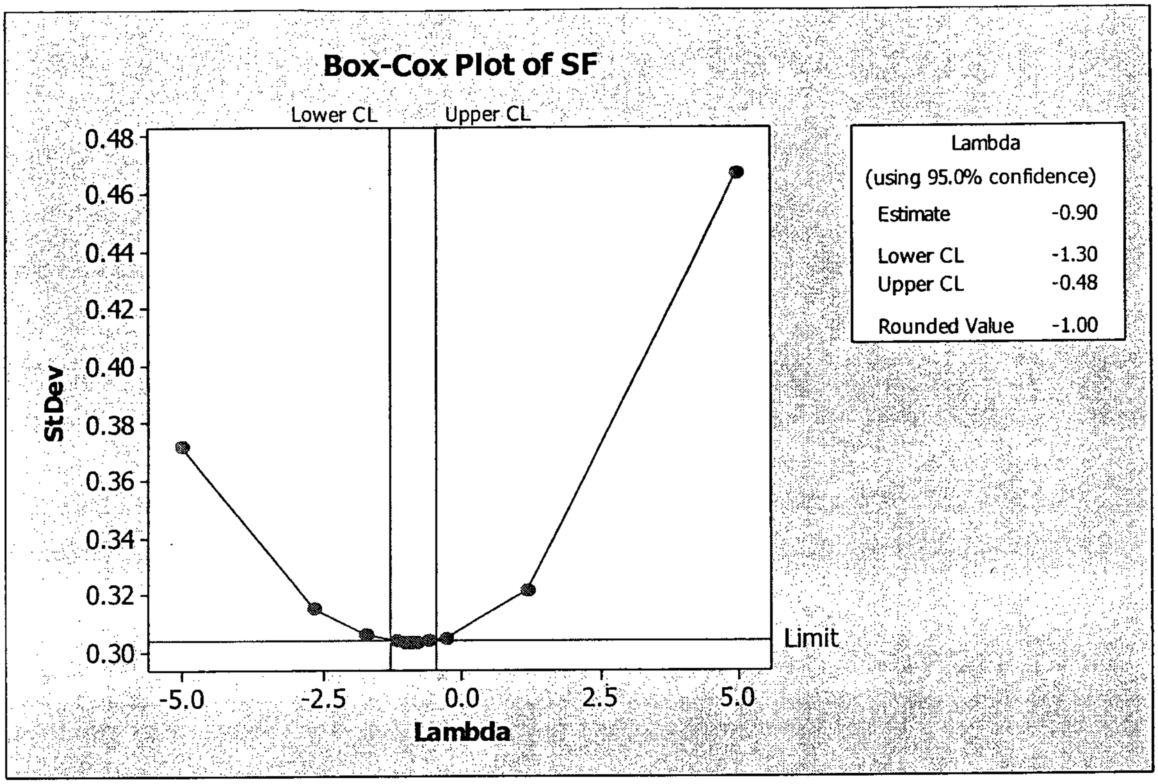
Box-Cox Power Transformation

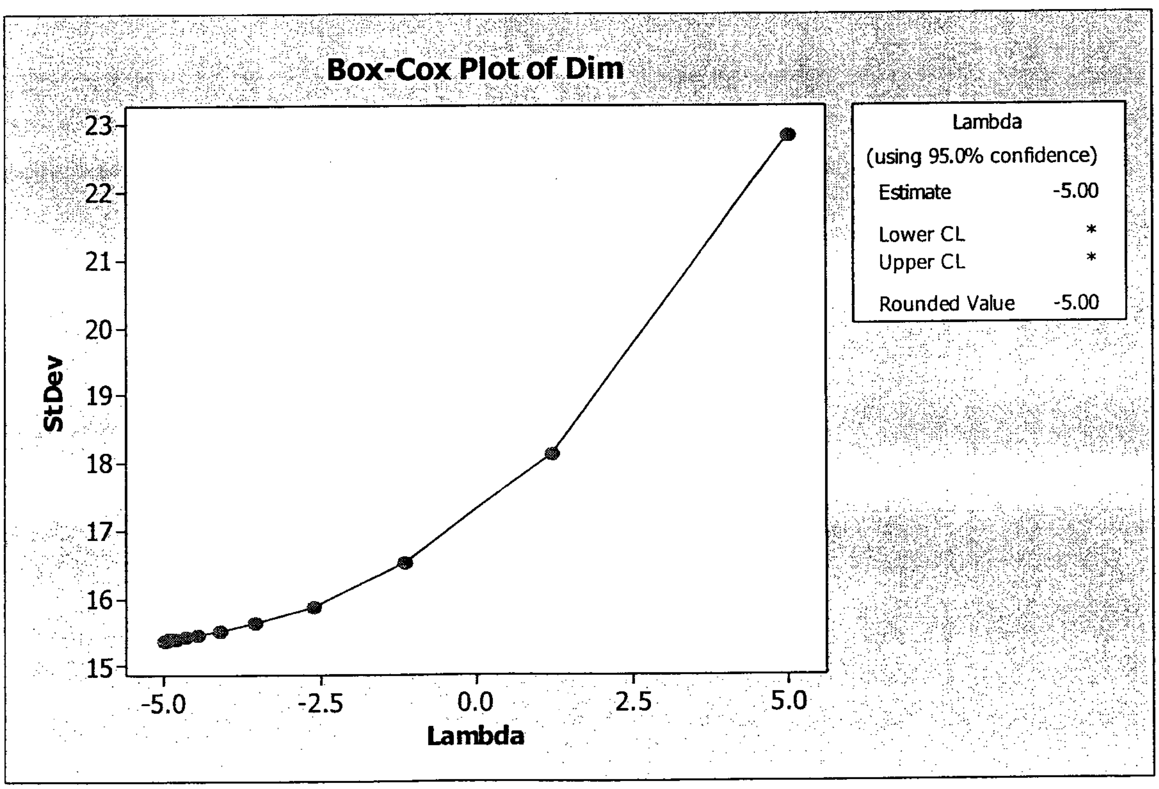




Appendix D

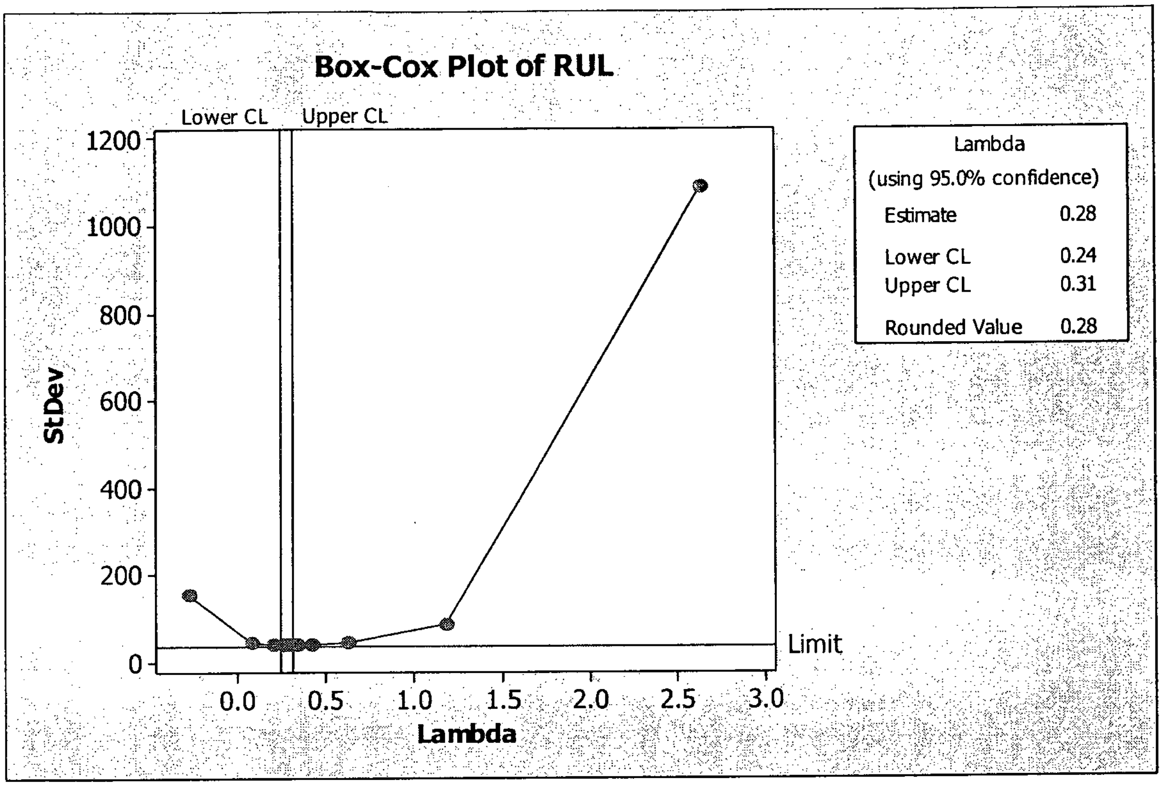
Box-Cox Power Transformation





Appendix D

Box-Cox Power Transformation



Appendix D

Sample of a Trial for Test of Significance

Predictor	Coef	SE Coef	t	P
Constant	4.83	0.647	7.465224	0
D	0.001	0.0007	1.428571	0.158
t	-0.08	0.042	-1.90476	0.048
C	1.12	0.0478	23.43096	0
$A^{0.5}$	-0.35	0.094	-3.7234	0
S	0.01	0.003	3.333333	0
R	0.001	0.0007	1.428571	0.26
pH	0.21	0.0145	14.48276	0
$(\rho)^{-0.23}$	-18.4	0.533	-34.5216	0
1/K	-3.61	0.326	-11.0736	0
Loge W	-0.19	0.08	-2.375	0.006
P^2	-0.0001	0.00001	-10	0.96
1/SF	-0.66	0.23	-2.86957	0.004

Predictor	Coef	SE Coef	t	P
Constant	6.75	1.08	6.25	0
C	1.03	0.02	47.14	0
$A^{0.5}$	-0.28	0.08	-3.5	0.001
S	0.01	0.003	3.333333	0
pH	0.22	0.0145	15.17241	0
$(\rho)^{-0.23}$	-18	0.527	-34.1556	0
1/K	-3.5	0.326	-10.7362	0
Loge W	-0.2	0.07	-2.85714	0.005
1/SF	-0.28	0.14	-2	0.004

Appendix D

Sample of BPNN Trial

Training Patterns	425
Testing Patterns	142
Validation Patterns	142

	Input Layer	Hidden Layer	Output Layer
Neurons	15	30	1
Function	[-1, 1]	Gaussian	Linear

Learning rate	0.1
Momentum	0.3
Initial Weight	0.3

R^2 for Training	0.61
R^2 for Validation	0.58

Final Model of BPNN

Training Patterns	408
Testing Patterns	136
Validation Patterns	136

	Input Layer	Hidden Layer	Output Layer
Neurons	8	24	1
Function	[-1, 1]	Gaussian	tansh

Learning rate	0.058
Momentum	0.268
Inetial Weight	0.3

R^2 for Training	0.96
R^2 for Validation	0.91

Appendix D

Sample of GRNN Trial

Training Patterns	425
Testing Patterns	142
Validation Patterns	142

	Input Layer	Hidden Layer	Output Layer
Neurons	15	425	1
Function	[-1, 1]	Gaussian	

Smoothing Factor	0.3
Distance metric	Euclidean
Calibration	Genetic adaptive

R^2 for Training	0.51
R^2 for Validation	0.44

Final Model of GRNN

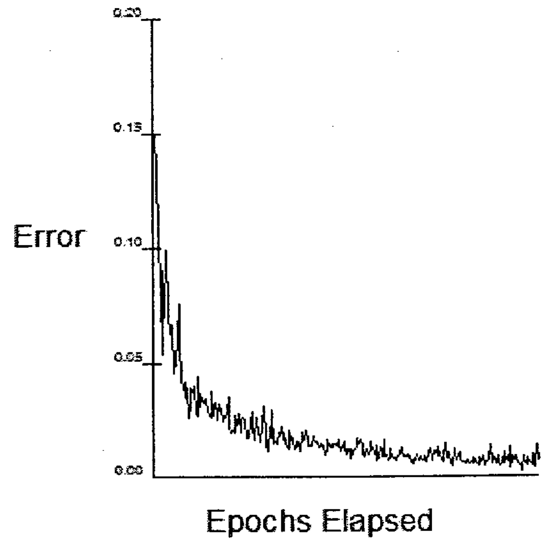
Training Patterns	408
Testing Patterns	136
Validation Patterns	136

	Input Layer	Hidden Layer	Output Layer
Neurons	8	408	1
Function	[-1, 1]	Gaussian	

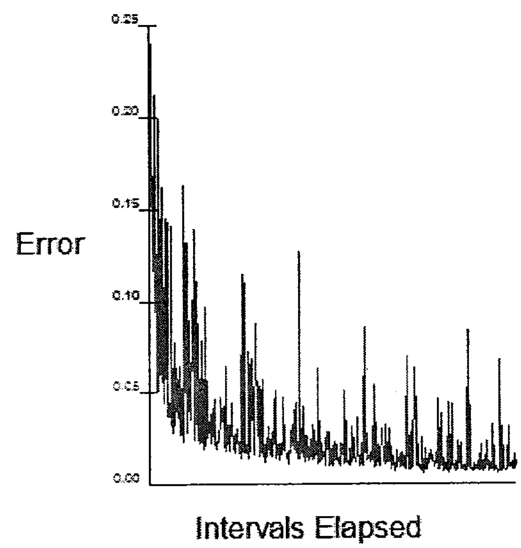
Smoothing Factor	0.14
Distance metric	Euclidean
Calibration	Genetic adaptive

R^2 for Training	0.95
R^2 for Validation	0.89

Appendix D

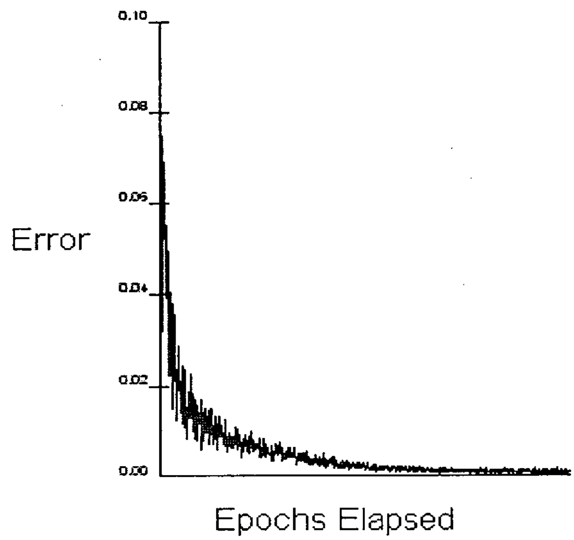


Sample for Error Gradient for a Training Trial

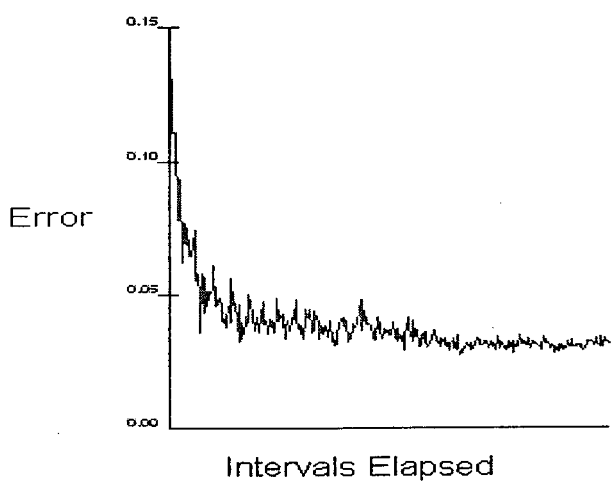


Sample for Error Gradient for a Validation Trial

Appendix D

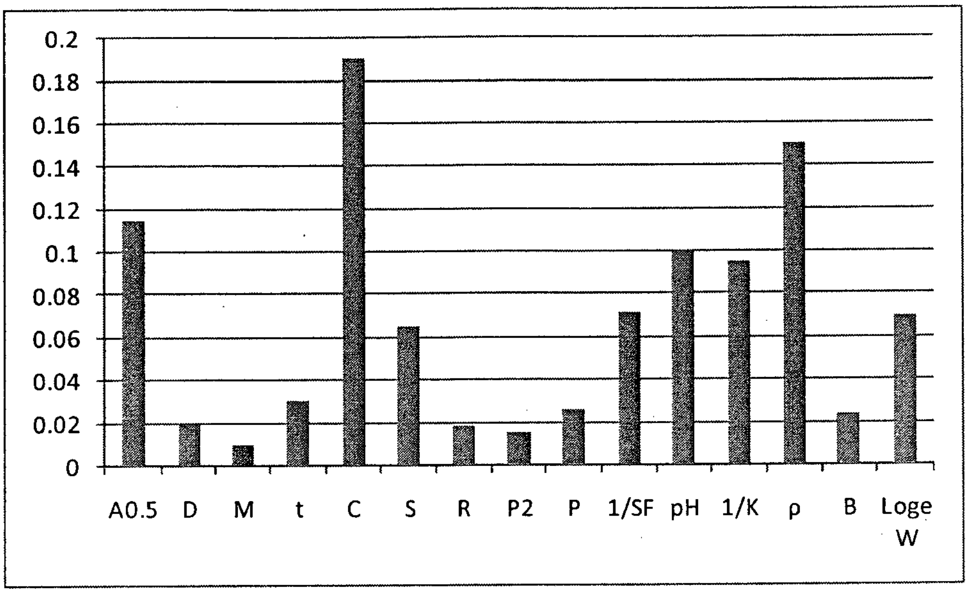


Sample for Error Gradient of Training Set for a final Model

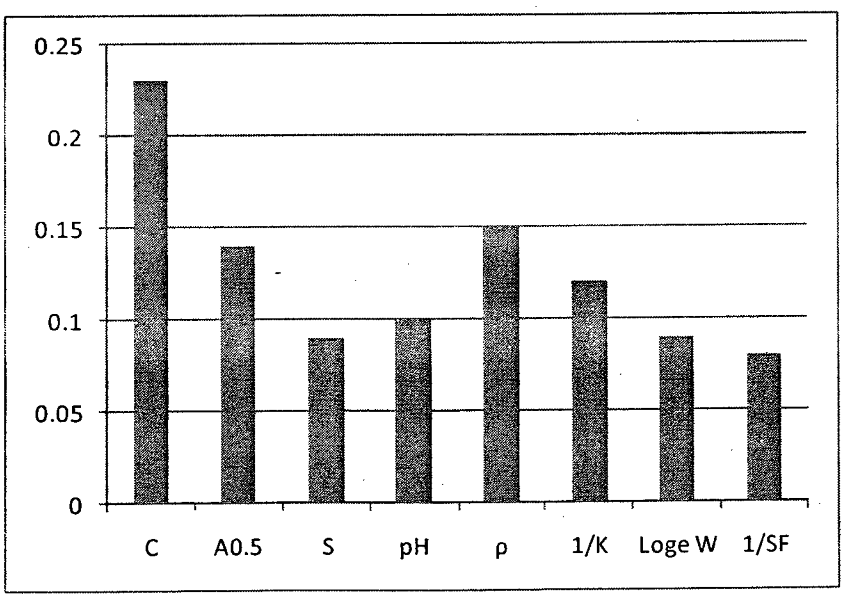


Sample for Error Gradient of Validation Set for a Final Model

Appendix D



Sample of a Trial Shows Contribution Values for Inputs



Contribution Values for Final Model

Appendix E

Sample of Analysis of Moncton Water Main Data

Data of Total Water Main Network			Data of Partial Water Main Network	
Material	Length(m)	Number of Breaks	Length(m)	Number of Breaks
Cast iron	199,457	2,580	107,507	1,392
A.C.		2		
Asbestos	12,439	32	6,578	25
Blue Brute		3		
Concrete	30,149	2	12,381	1
Copper	537	40		
Ductile	139,825	50	43,313	215
Galvanized		7		
Hyprescon		9		
Lead		10		
PVC	128,375	4	3,091	19
Steel		2		
Unknown	7,028	63		
Total	517,811	2,804	172,870	1,652

Appendix E

Type of Availabele Data from Moncton and Ste-Froy

Data	Quebec(Ste-Froy)	Moncton
Pipe Material	Yes	Yes
Pipe Diameter	Yes	Yes
Pipe Length	Yes	Yes
Year of Installation/Pipe Age	Yes	Yes
Pipe Depth	Yes	No
Breaks History of Individual Pipes	Yes	Yes
Type of Breaks	Yes	Yes
GIS	Yes	Partial
Soil	No	Yes
Cathodic Protection for Metallic Pipes	No	No
Pavement	No	Partial
Replacement Records	No	No
Other Operation/Maintenance Records (Pressure, Flushing)	No	No

Appendix E

Number of Breaks

Diameter (mm)		100	100	100	100	100	100	100	100	100	150	150	150	150	150	150
Year Installed		1954	1955	1958	1959	1960	1961	1963	1964	1965	1940	1951	1952	1953	1954	1955
Total Length (m)		455	78	48	92	48	99	259	575	187	305	1293	2436	712	11022	4115
No. of Breaks by Year	1987								1			1	1		5	
	1988							2				2			7	1
	1989	1							2				1	1	8	3
	1990	1				1						2	1		4	
	1991						1		1			1		1	8	6
	1992							1	1		2	2	1		5	3
	1993											1	1		9	3
	1994								2				2	1	5	
	1995												1		6	2
	1996											1	2		7	1
	1997	1					1		1						2	3
	1998												2		7	
	1999	1											2		11	
	2000														9	2
	2001		1			1									2	
Total	755	4	1	0	0	2	2	3	8	0	2	10	14	3	95	24

Grey Cast Iron Pipes Total No of Breaks (1987-2001) by Individual Pipes

Total Number of Break	Pipe ID	Length (m)	Type of Break	Date of Break	Date of Installation	Material	Diameter(mm)
3	4477	57	Principle branch joint	1997-5-31	1960-1-1	Grey Cast Iron	150
	4477	57	Perforation	1999-10-8	1960-1-1	Grey Cast Iron	150
	4477	57	Perforation	2000-1-18	1960-1-1	Grey Cast Iron	150
1	4523	92	Joint	1993-4-27	1955-1-1	Grey Cast Iron	250
2	4538	61	circumferential	1995-4-29	1960-1-1	Grey Cast Iron	150
	4538	61	circumferential	1996-10-25	1960-1-1	Grey Cast Iron	150
1	4831	80	Joint	1989-3-15	1904-1-1	Grey Cast Iron	150
2	4867	24	Perforation	1989-3-10	1965-1-1	Grey Cast Iron	250
	4867	24	Fire hydrant joint	1994-1-21	1965-1-1	Grey Cast Iron	250
1	4876	17	circumferential	1995-9-19	1960-1-1	Grey Cast Iron	250
6	5009	15	circumferential	1987-1-9	1960-1-1	Grey Cast Iron	250
	5009	15	circumferential	1988-7-4	1960-1-1	Grey Cast Iron	250
	5009	15	circumferential	1990-7-3	1960-1-1	Grey Cast Iron	250
	5009	15	Perforation	1994-6-21	1960-1-1	Grey Cast Iron	250
	5009	15	circumferential	1995-2-17	1960-1-1	Grey Cast Iron	250
	5009	15	circumferential	1995-11-9	1960-1-1	Grey Cast Iron	250

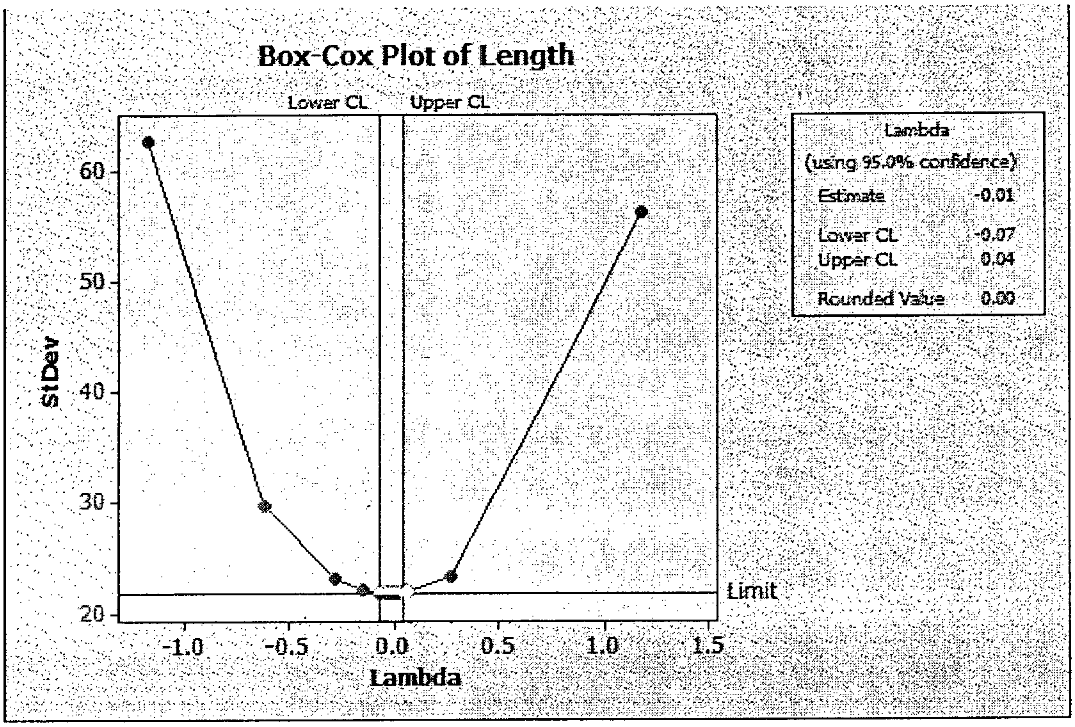
Appendix E

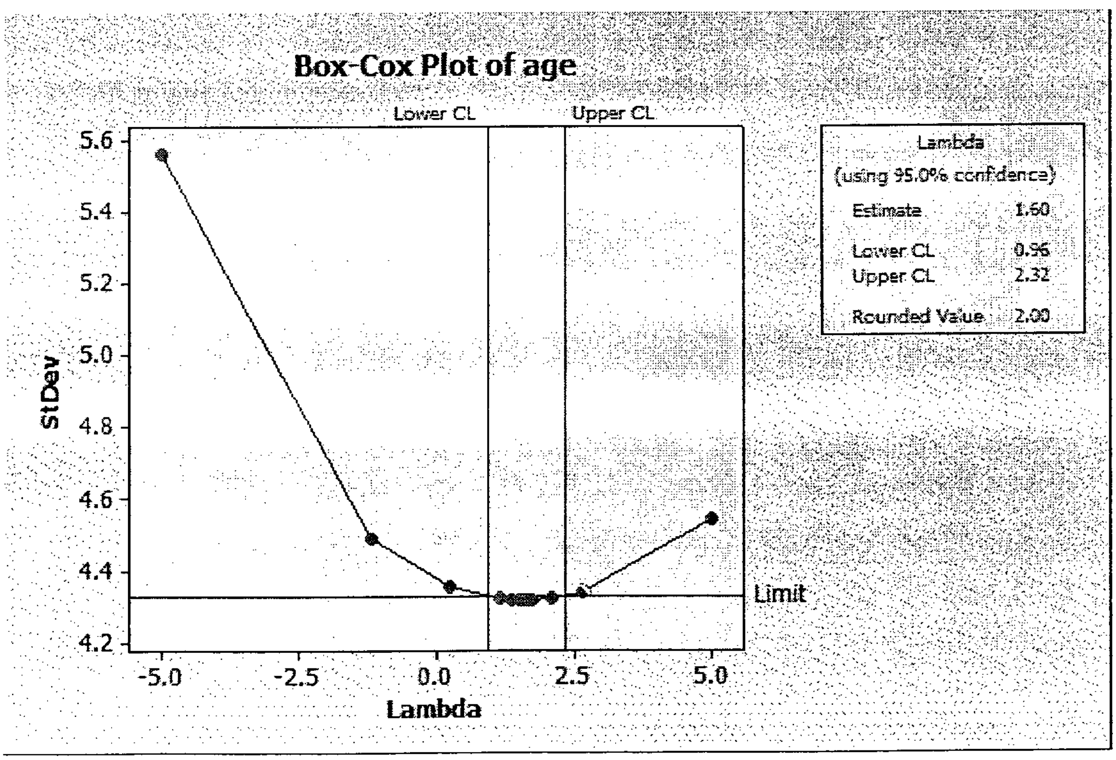
Break Rate /Km

Pipe Characteristics			Break Rate- No. of Breaks/ Km														
Pipe Diameter (mm)	Decades Pipe Installed	Length (Km)	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
All	All	130	0.35	0.45	0.48	0.38	0.45	0.45	0.52	0.48	0.37	0.3	0.41	0.42	0.31	0.31	0.13
100	1950s	1.1	1.82	0.91	0.91	0.91	0	0	0	0	0	0	0.91	0	0.91	0	0.91
100	1960s	1.17	0.86	1.71	1.71	0.86	1.71	1.71	0	1.71	0	0	1.71	0	0	0	0.86
150	1950s	35.42	0.45	0.51	0.56	0.45	0.73	0.56	0.79	0.42	0.42	0.48	0.4	0.4	0.45	0.45	0.14
150	1960s	37.01	0.41	0.59	0.51	0.43	0.62	0.54	0.73	0.7	0.49	0.3	0.46	0.84	0.43	0.27	0.22
200	1950s	11.63	0.17	0.52	0.43	0.34	0.34	0.34	0.34	0.43	0.43	0.34	0.6	0.17	0.26	0.43	0.09
200	1960s	11.17	0.36	0.36	0.27	0.36	0	0.54	0.27	0.45	0.09	0.36	0.36	0.36	0	0.09	0.09
250	1950s	4.36	0.21	0.62	1.03	0.21	0.21	0	0.21	0.21	0	0.21	0.21	0	0.21	0.62	0
300	1960s	3.46	0.29	0	0	0	0	0.29	0	0.29	0.29	0	0.58	0	0	0.29	0
300	1950s	2.59	0.39	0	0.77	0.77	0	0	0.77	0.77	0	0	0	0.39	0.39	0	0
350&400	1950s&1960s	5.44	0.18	0	0	0.18	0	0.18	0	0	0	0	0.18	0	0	0	0
500+	1940s-1970s	4.31	0	0	0.23	0	0	0	0.23	0	0	0.23	0.46	0	0	0	0

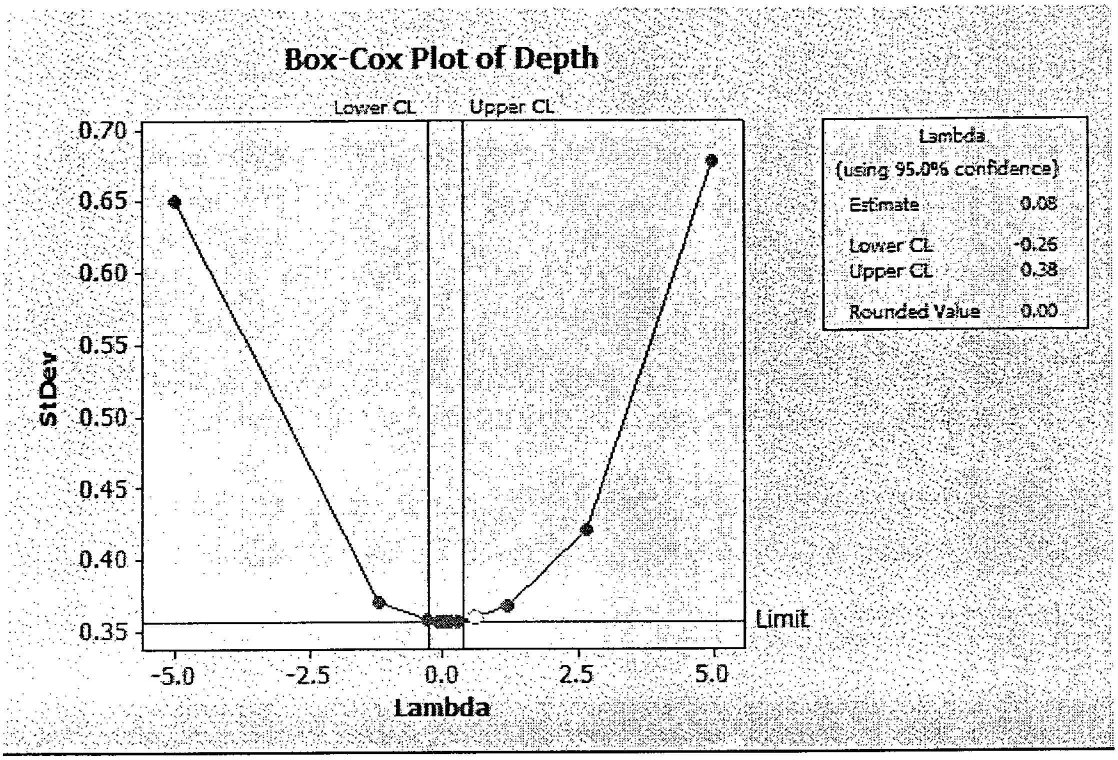
Appendix E

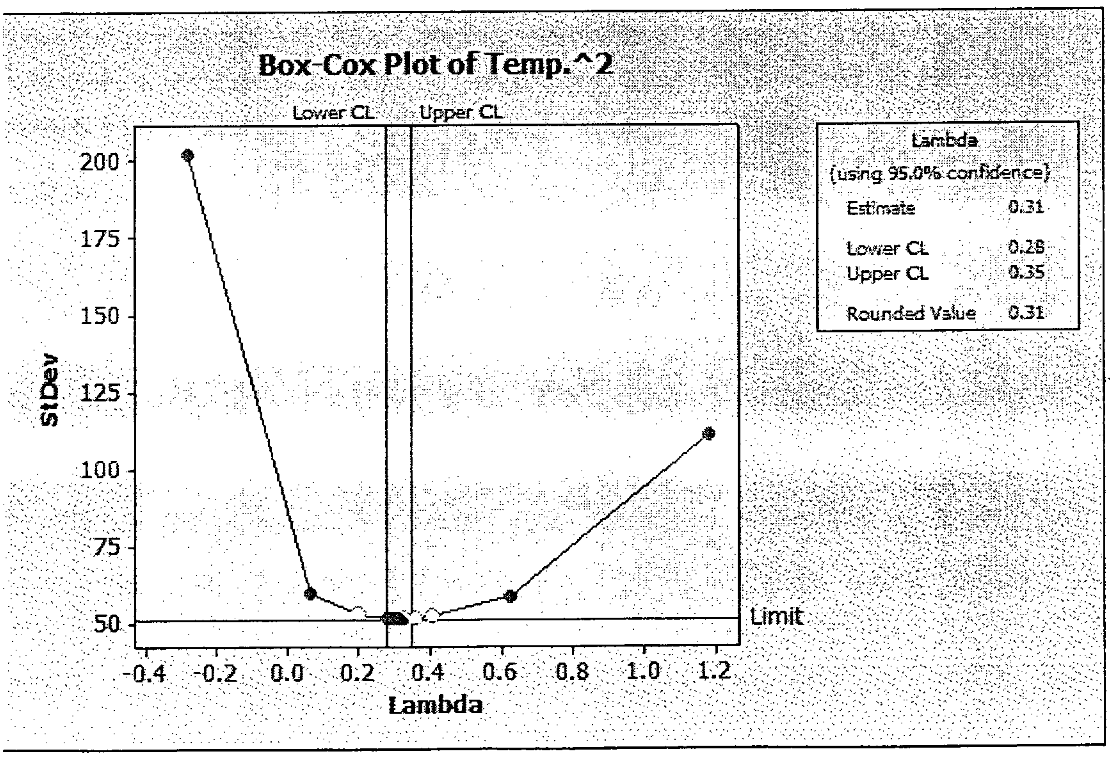
Box-Cox Transformation for the Input Parameter of the Failure Rate Model



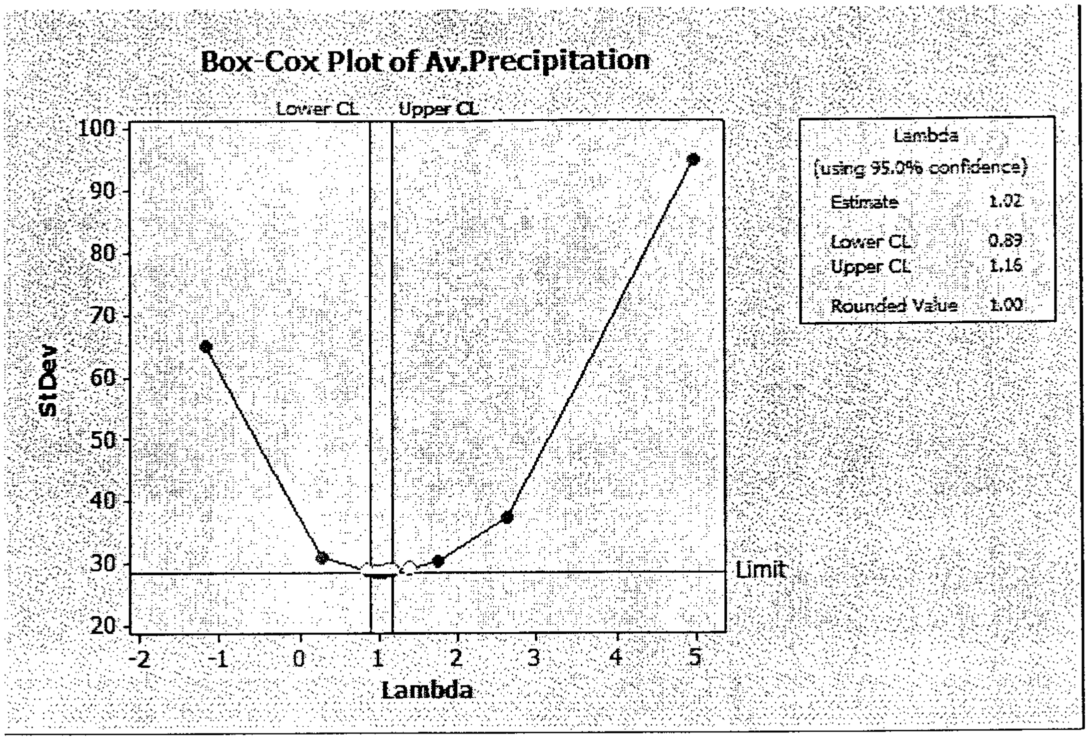


Appendix E

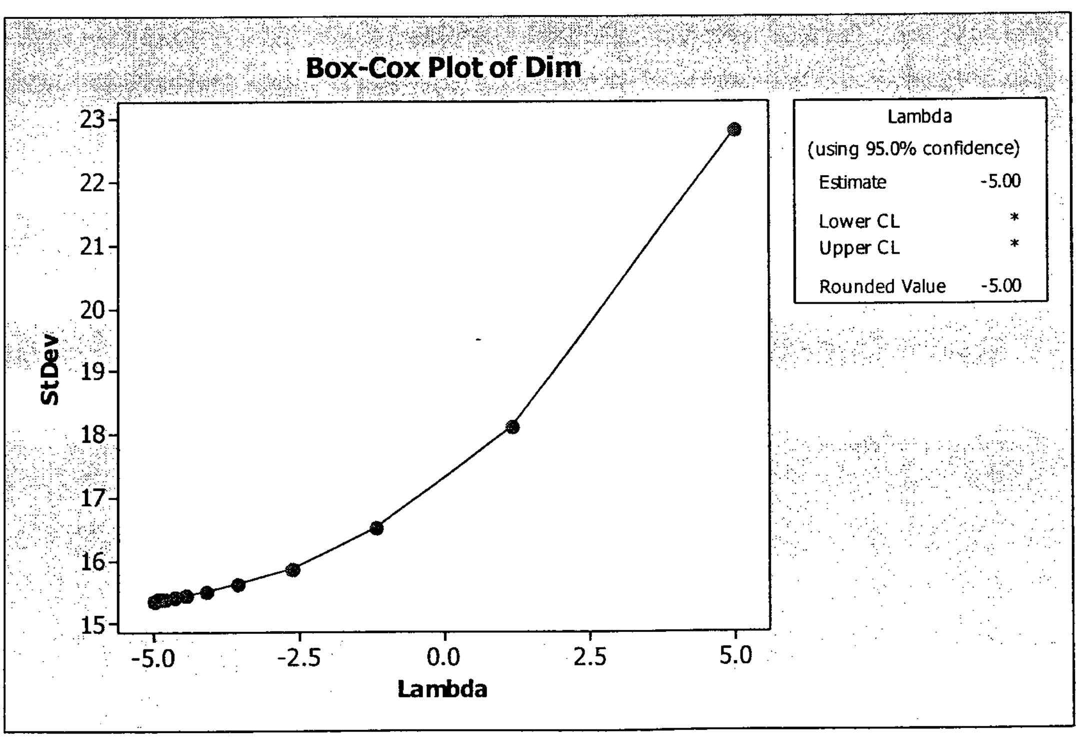

Box-Cox Plot of Depth
Lower CL
Upper CL
Lambda
(using 95.0% confidence)
Estimate 0.08
Lower CL -0.26
Upper CL 0.38
Rounded Value 0.00
StDev
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0.35
Limit
-5.0
-2.5
0.0
2.5
5.0
Lambda


Box-Cox Plot of Temp.^2
Lower CL
Upper CL
Lambda
(using 95.0% confidence)
Estimate 0.31
Lower CL 0.28
Upper CL 0.35
Rounded Value 0.31
StDev
200
175
150
125
100
75
50
Limit
-0.4
-0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Lambda

Appendix E

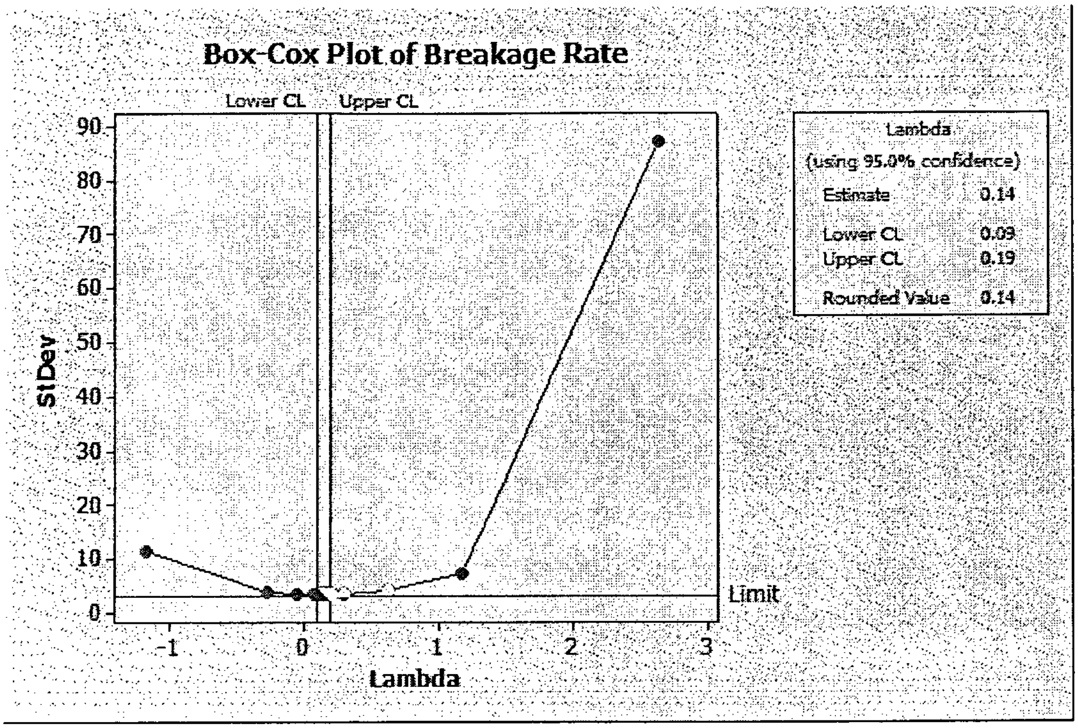


Box-Cox Plot of Av.Precipitation
Lower CL
Upper CL
Lambda
(using 95.0% confidence)
Estimate 1.02
Lower CL 0.89
Upper CL 1.16
Rounded Value 1.00
Limit
StDev
Lambda



Box-Cox Plot of Dim
Lambda
(using 95.0% confidence)
Estimate -5.00
Lower CL *
Upper CL *
Rounded Value -5.00
StDev
Lambda

Appendix E



Selection of the Best Subset

Vars	R^2	Mallows Cp	S	Dim	L	D	T^2	Pr	Log_e (L)	A^2	Log_e (D)	$(T)^{1.24}$
1	79.1	646	3.74						x			
1	40.1	3140	6.32		x							
2	86.3	181.4	3.02		x				x			
2	81.9	465.5	3.47						x		x	
3	87.3	125.4	2.9		x				x		x	
3	87.2	128.6	2.9		x				x			x
4	88.2	68.4	2.81		x				x		x	x
4	88.1	73	2.77		x		x		x		x	
5	88.5	47.4	2.78		x	x			x		x	x
5	88.5	50.1	2.74		x	x	x		x		x	
6	88.8	30.3	2.74		x	x	x	x	x		x	
6	89	34	2.71		x	x		x	x		x	x
7	89	19.2	2.72		x	x	x		x	x	x	
7	89	21	2.69		x	x			x	x	x	x
8	89.1	7.7	2.7		x	x	x	x	x	x	x	
8	89.1	13.8	2.69		x	x		x	x	x	x	x
9	89.1	9.2	2.69		x	x	x	x	x	x	x	x
9	89.1	9.3	2.69	x	x	x	x	x	x	x	x	
10	89.3	11	2.69	x	x	x	x	x	x	x	x	x

Appendix E

Sample of BPNN Trial

Training Patterns	430
Testing Patterns	143
Validation Patterns	143

	Input Layer	Hidden Layer	Output Layer
Neurons	11	32	1
Function	[-1, 1]	Logistic	Linear

Learning rate	0.1
Momentum	0.3
Initial Weight	0.3

R^2 for Training	0.67
R^2 for Validation	0.61

Final Model of BPNN

Training Patterns	420
Testing Patterns	140
Validation Patterns	140

	Input Layer	Hidden Layer	Output Layer
Neurons	9	24	1
Function	[-1, 1]	Gaussian	tansh

Learning rate	0.062
Momentum	0.28
Initial Weight	0.3

R^2 for Training	0.95
R^2 for Validation	0.88

Appendix E

Sample of BPNN Trial

Training Patterns	430
Testing Patterns	143
Validation Patterns	143

	Input Layer	Hidden Layer	Output Layer
Neurons	11	430	1
Function	[-1, 1]	Gaussian	

Smoothing Factor	0.25
Distance metric	Euclidean
Calibration	Genetic adaptive

R^2 for Training	0.68
R^2 for Validation	0.63

Final Model of GRNN

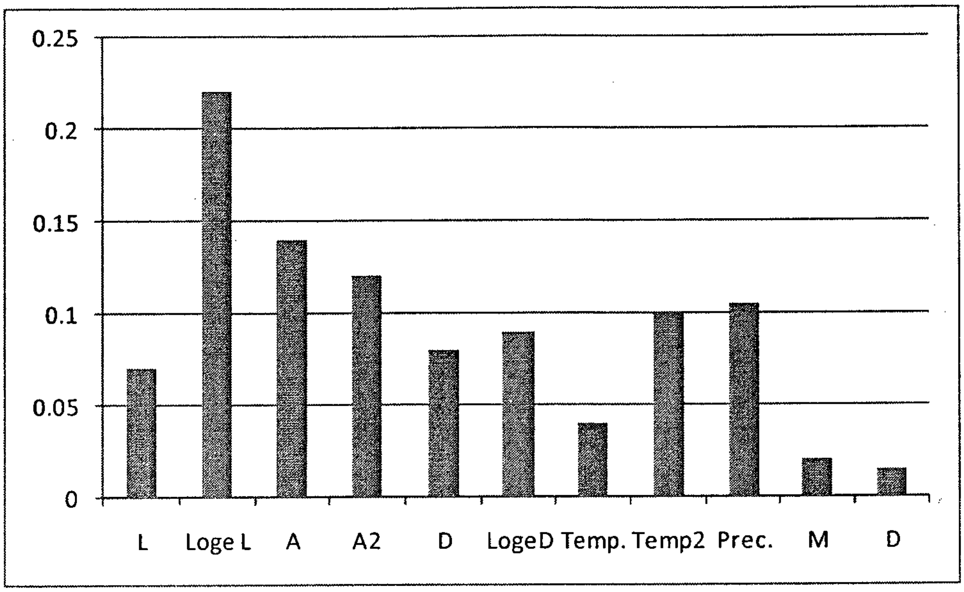
Training Patterns	420
Testing Patterns	140
Validation Patterns	140

	Input Layer	Hidden Layer	Output Layer
Neurons	9	420	1
Function	[-1, 1]	Gaussian	

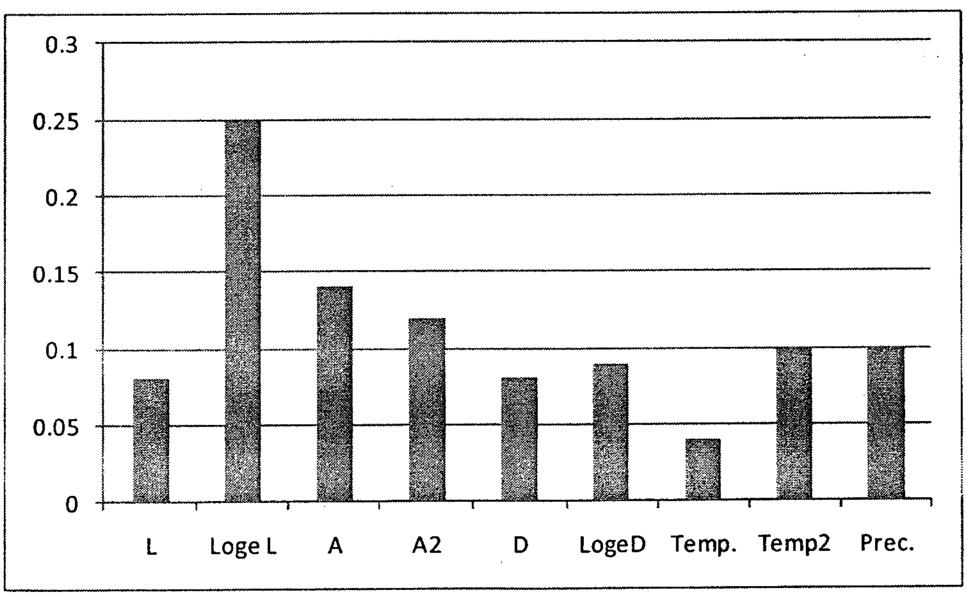
Smoothing Factor	0.125
Distance metric	Euclidean
Calibration	Genetic adaptive

R^2 for Training	0.96
R^2 for Validation	0.89

Appendix E



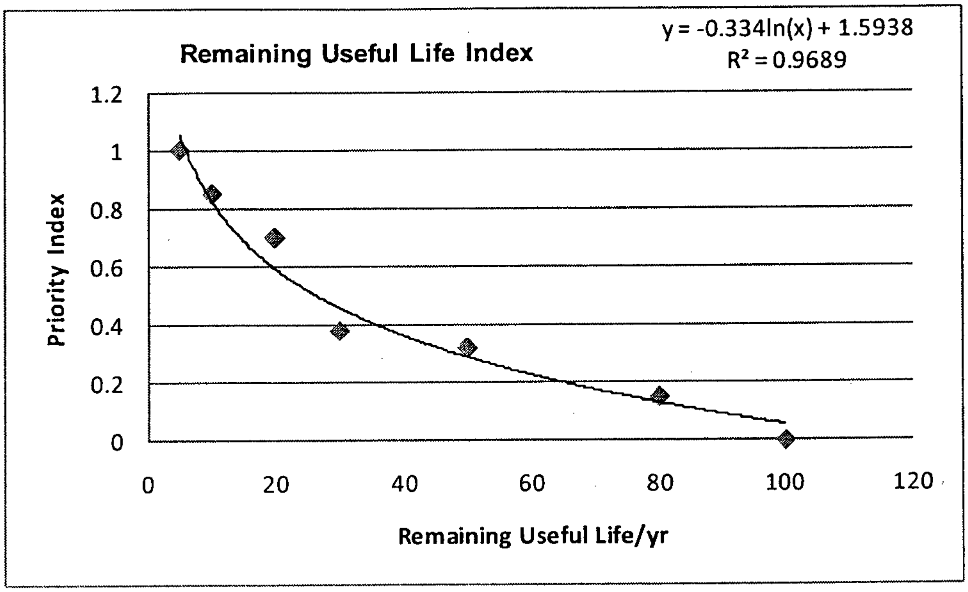
Contribution of the Input Variables Considered in a Trial

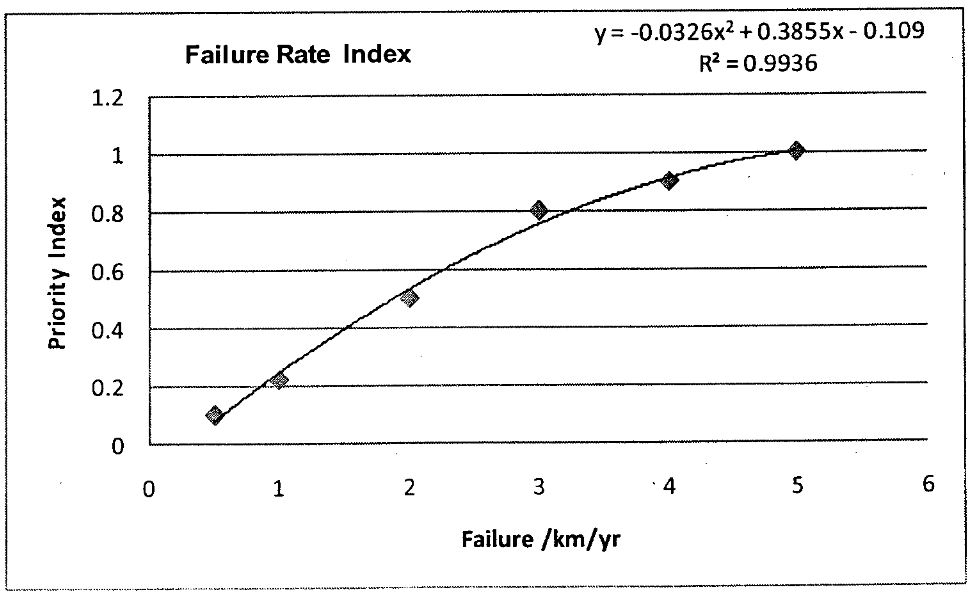


Contribution of the Final Input Variables Considered

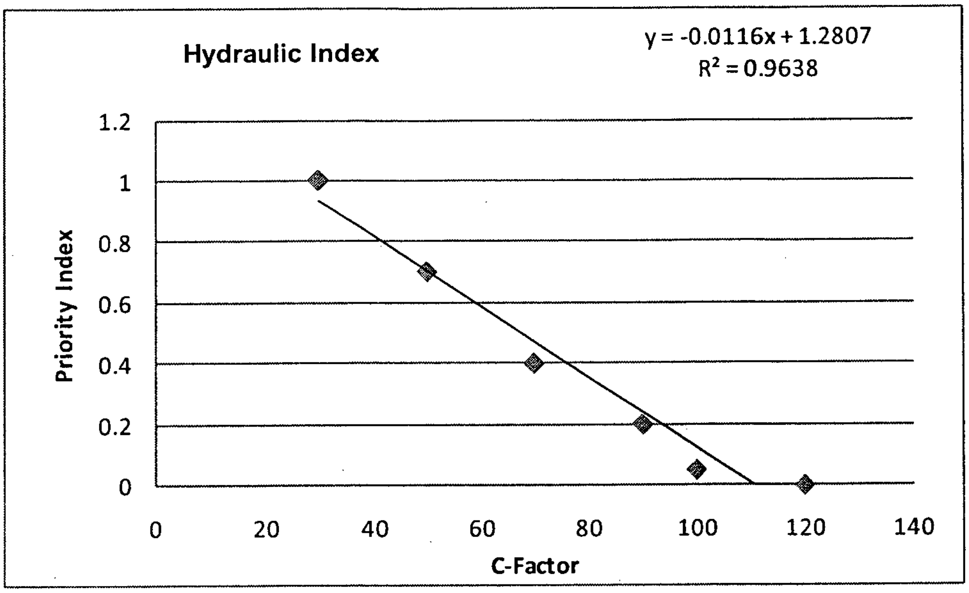
Appendix F

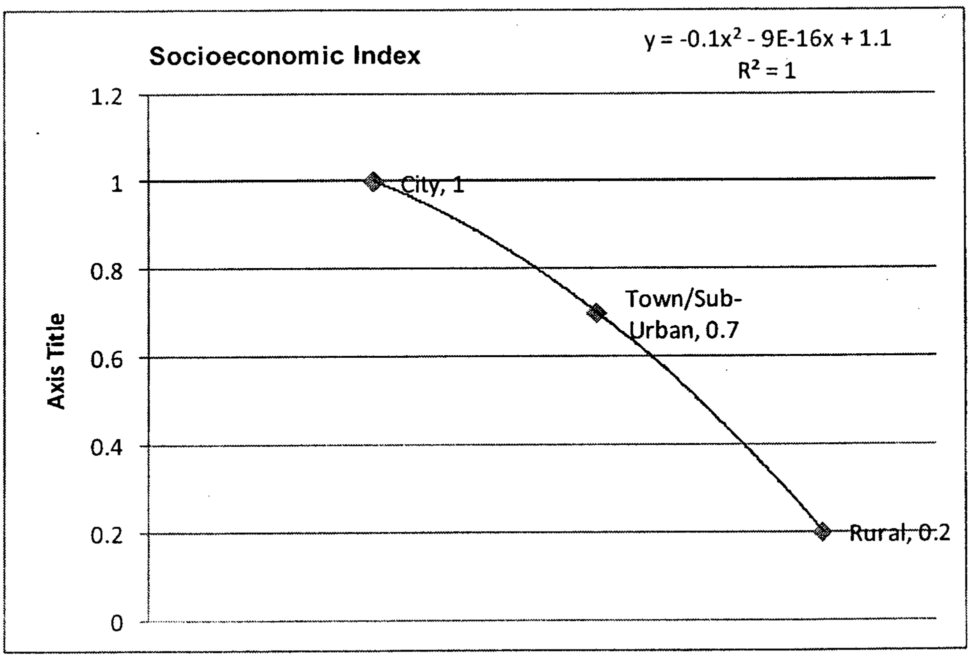
Priority Indexes for Condition Rating



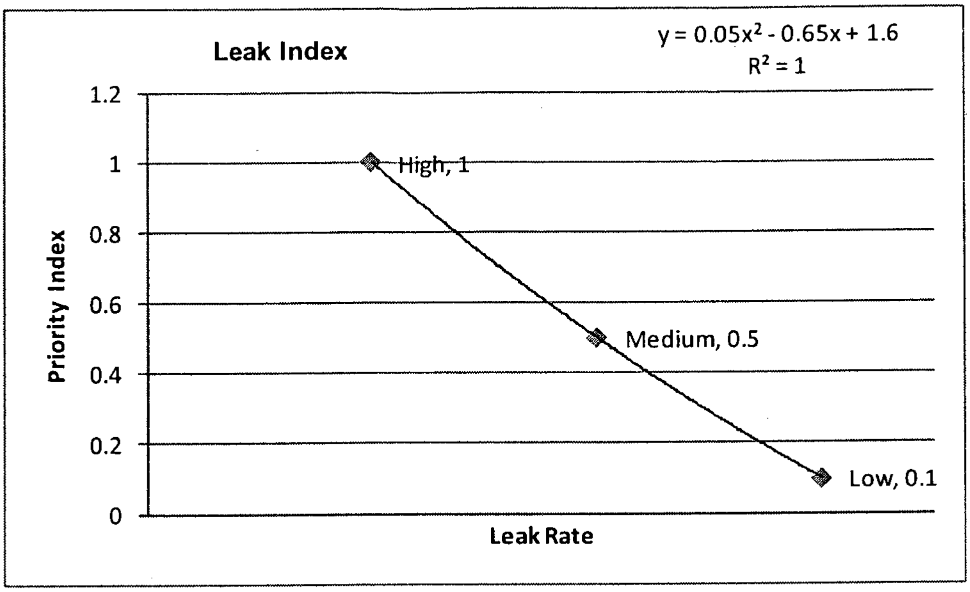


Appendix F

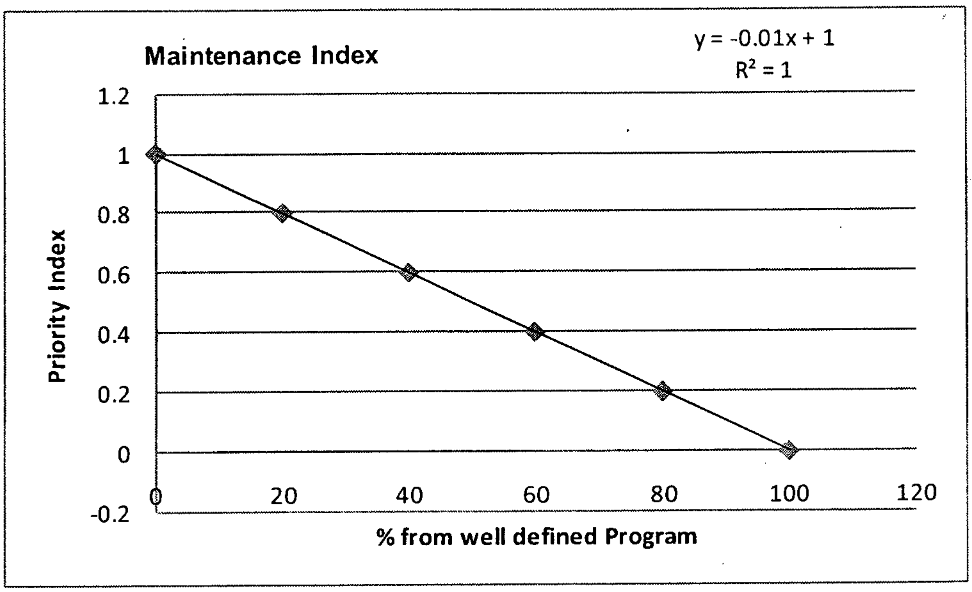

Hydraulic Index
y = -0.0116x + 1.2807
R² = 0.9638
1.2
1
0.8
0.6
0.4
0.2
0
Priority Index
0
20
40
60
80
100
120
140
C-Factor


Socioeconomic Index
y = -0.1x² - 9E-16x + 1.1
R² = 1
1.2
1
0.8
0.6
0.4
0.2
0
Axis Title
City, 1
Town/Sub-Urban, 0.7
Rural, 0.2

Appendix F



Leak Index
y = 0.05x² - 0.65x + 1.6
R² = 1
1.2
1
0.8
0.6
0.4
0.2
0
Priority Index
High, 1
Medium, 0.5
Low, 0.1
Leak Rate



Maintenance Index
y = -0.01x + 1
R² = 1
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
Priority Index
0
20
40
60
80
100
120
% from well defined Program

Appendix F

Relative Weights for Condition Assessment

Factor	Ref. 1	Ref. 2	Ref. 3	Ref. 4	Ref. 5	Ref. 6
Leak Rate	0.26	0.22	0.23	0.25	0.24	0.26
RUL	0.22	0.23	0.25	0.17	0.18	0.24
Failure Rate	0.19	0.19	0.18	0.22	0.23	0.2
Socioeconomic	0.12	0.15	0.15	0.14	0.15	0.12
Maintenance	0.11	0.12	0.09	0.14	0.11	0.1
Hydraulic	0.1	0.09	0.1	0.08	0.09	0.08

Factor	Ref. 7	Ref. 8	Ref. 9	Ref. 10	Ref. 11	Ref. 12
Leak Rate	0.21	0.27	0.23	0.25	0.28	0.264
RUL	0.25	0.22	0.19	0.19	0.21	0.21
Failure Rate	0.22	0.19	0.23	0.2	0.19	0.18
Socioeconomic	0.14	0.15	0.17	0.16	0.14	0.17
Maintenance	0.08	0.07	0.09	0.12	0.11	0.07
Hydraulic	0.1	0.1	0.09	0.08	0.07	0.11

Average Relative Weights