# WATER DISTRIBUTION SYSTEM FAILURES: AN INTEGRATED FRAMEWORK FOR PROGNOSTIC AND DIAGNOSTIC ANALYSES

by

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# ABSTRACT

The main goal of this research is to develop an integrated decision support system framework for prognostic and diagnostic analyses of water distribution system (WDS) failures. The interventions based on the prognostic analysis will reduce the likelihood of failures, and in case of a failure, will minimize the consequences of the failures. The framework consists of five novel models. For prognostic analysis, the first model evaluates the reliability of WDS in terms of *utility* and *belief* of the estimated utility. This model provides a measure of degree of uncertainties in reliability estimation and helps to plan and design a reliable WDS. Based on various influencing factors, the leakage potential model evaluates potential for leakage under varying operating conditions. Based on identified *symptoms* of failure such as taste and odor, and the *causes* of failure such as free residual chlorine, the water quality failure potential model evaluates the potential for water quality failure (WQF).

For diagnostic investigation, the leakage location and detection model, the fourth model, identifies the presence of an actual leakage, if any, and the most probable leakage location in WDS. The WQF detection model, the fifth model, identifies the most vulnerable location in the WDS and in case of failure, identifies the most probable reason and most probable source of water quality failure.

Finally, based on the developed models and other external information, an integrated prognostic and diagnostic decision support system framework has been developed. The prognostic capabilities of the framework provide states of the WDS and evaluate failure potentials of the system. The diagnostic capabilities of the framework help to reduce false positive and false negative predictions, and identify the failure location with minimal time after the occurrence which minimizes the consequences of failure. The framework has 'unique' capacity to bring the modelling information (hydraulic and Quality), consumer complaints and laboratory test information under a single platform. The outcomes of this research widely addressed the uncertainties associated with WDS which improves the efficiency and effectiveness of diagnosis and prognosis analyses of WDS failures. The research also provides new insights on how to incorporate fuzzy set in the assessment of WDS failures. It is expected that the developed integrated framework will help municipalities to make informed decisions to increase the safely and the security of public health.

# PREFACE

I, Mohammad Shafiqul Islam, conceived and developed all the contents in this thesis under the supervision of Dr. Rehan Sadiq. The other coauthors of the articles based on this thesis, Dr. Alex Francisque, Dr. Manuel J. Rodriguez, Dr. Homayoun Najjaran and Dr. Mina Hoorfar, have reviewed all the manuscripts prepared and provided critical feedback to improve the quality of the manuscripts and thesis. Most of the contents of this thesis are published, accepted or submitted for publication in scientific international journals and conferences.

- A version of Chapter 2 has been submitted for publication in *The special issue of the Journal of Tunnelling and Underground Space Technology (TUST) incorporating Trenchless Technology Research* with the title "Water Distribution System Failure: A Forensic Analysis" (Islam et al. 2011a). This article is under second review.
- A version of Chapter 3 has been submitted for publication in *ASCE Journal of Water Resources Planning and Management* with the title "Reliability Assessment for Water Supply Systems: A Novel Methodology" (Islam et al. 2012b). This paper is under second review.
- A version of Chapter 4 has been published in *Journal of Water Supply: Research and Technology – AQUA* with the title "Evaluating Leakage Potential in Water Distribution Systems: A Fuzzy-Based Methodology"(Islam et al. 2012a).
- A version of Chapter 5 has been published in *The Urban Water Journal* with the title "Leakage Detection and Location in Water Distribution System using a Fuzzy-Based Methodology" (Islam et al. 2011b).
- A version of Chapter 6 has been submitted for publication in *Water Resource Management* with the title "Evaluating Water Quality Failure Potential in Water Distribution Systems: A Fuzzy-TOPSIS-OWA Based Methodology" (Islam et al. 2011c).
- Some portions of Chapter 4 and Chapter 5 have been published in *The Proceedings of the 20th Canadian Hydrotechnical CSCE Conference (2011)* with the title "Leakage Forensic Analysis for Water Distribution Systems: A Fuzzy-Based Methodology" (Islam et al. 2011d).

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| | |
|---|---|
| A&E | Accident And Emergency |
| AC | Asbestos Cement |
| ADB | Asian Development Bank |
| AHP | Analytical Hierarchy Process |
| ALC | Active Leakage Control |
| ALR | Awareness, Location, And Repair Time |
| ANN | Artificial Neural Network |
| ANP | Analytic Network Process |
| APHA | American Public Health Association |
| AWWA | American Waterworks Association |
| BABE | Burst And Background Estimates |
| BPA | Basic Probability Assignment Function |
| CDF | Cumulative Distribution Function |
| CI | Cast Iron |
| CIS | Customer Information System |
| COG | Centre Of Gravity |
| CPU | Central Processing Unit |
| DBP | Disinfectant By-Products |
| DMA | District Metered Area |
| DMA | Demand Multiplier |
| DO | Dissolve Oxygen |
| DSS | Decision Support System |
| EIC | Equivalent Illness Complaints |
| ELECTRE | ELimination Et Choix Traduisant la REalite |
| EPS | Extended Period Simulation |
| ESC | Equivalent On Spot Complaints |
| FNIS | Fuzzy Negative Ideal Solution |
| FORM | First Order Reliability Method |
| FOSM | First-Order Second-Moment |
| FPIS | Fuzzy Positive Ideal Solution |
| FRB | Fuzzy Rule-Based |
| FRC | Free Residual Chlorine |
| GI | Galvanized Iron |
| GIS | Geographical Information System |
| GPRS | General Packet Radio Service |
| GSM | Global System For Mobile Communications |
| GWRC | Global Water Research Coalition |
| HPC | Heterotrophic Plate Count |
| ILP | Index Of Leakage Propensities |
| IWA | International Water Association |
| IWP | Institute of Water Policy, Philippine |
| LHS | Latin Hypercube Sampling |

| | |
|---|---|
| LP | Leakage Potential |
| MAUT | Multi-Attribute Utility Theory |
| MCDA | Multicriteria Decision Analysis |
| MCDM | Multi-Criteria Decision-Making |
| MCL | Maximum Contaminant Level |
| MCLG | Maximum Contaminant Level Goal |
| MF | Multiplying Factor |
| MIS | Management Information System |
| MISO | Multiple-Input Single-Output |
| MSX | Multi-Species-eXtension |
| MTBF | Mean Time Between The Failures |
| MWA | Metropolitan Water Authority Of Bangkok , Thailand |
| NOM | Natural Organic Matter |
| NRW | Non-Revenue Water |
| O&M | Operation & Maintenance |
| ORP | Oxidation Reduction Potential |
| OSWCA | Ontario Sewer and Water main Construction Association |
| OWA | Order Weighted Averaging |
| PAF | Pressure Adjustment Factor |
| PDF | Probability Distribution Function |
| PEST | Parameter Estimation |
| PROMETHEE | Preference Ranking Organization METHod for Enrichment Evaluations |
| PSTN | Public Switched Telephone Network |
| PVC | Polyvinyl Chloride |
| RIM | Regularly Increasing Monotone |
| RTU | Remote Telemetry Units |
| SHF | Structural and Associated Hydraulic Failure |
| SISO | Single-Input Single-Output |
| SMART | Simple Multi-Attribute Rating Technique |
| SRMSE | Square Root Of The Mean Square Error |
| TFN | Triangular Fuzzy Numbers |
| TOC | Total Organic Carbon |
| TOPSIS | Technique for Order Preference by Similarity to Ideal Solution |
| TSK | Takagi, Sugeno And Kang |
| TTHM | Total Tri-Halomethane |
| UNICEF | United Nations Children's Fund |
| USD | United States' Dollars |
| USEPA | United States Environmental Protection Agency |
| UTA | Utility Theory Additive |
| WDS | Water Distribution System |
| WHO | World Health Organization |
| WQF | Water Quality Failure |
| WSS | Water Supply System |
| WSSCC | Water Supply & Sanitation Collaborative Council |
| WSSD | Weighted Sum Of Squared Differences |
| ZFN | Trapezoidal Fuzzy Numbers |

# LIST OF SYMBOLS

| | |
|---|---|
| $A$ | Water age |
| $a$ | Lower level values of independent parameters |
| $A^+$ | Fuzzy positive ideal solution |
| $A^-$ | Fuzzy negative ideal solution |
| $A_{1\ to\ 4}$ & $B_{1\ to\ 3}$ | BPA mapping parameters |
| $b$ | The most likely values of independent parameters |
| $BB$ | Quality of pipe bedding and backfills |
| $c$ | Upper level values of independent parameters |
| $C$ | Quality of compaction |
| $CC$ | Closeness coefficients |
| $CD$ | Cover depth |
| $C_i$ | Discharge coefficient at node $i$ |
| $CoD$ | Commercial demand |
| $D$ | Demand |
| $\tilde{D}$ | Decision matrix |
| $D_i^+$ | Separation distance of alternatives from fuzzy positive ideal solution |
| $D_i^-$ | Separation distance of alternatives from fuzzy negative ideal solution |
| $DU(X)$ | Disutility Function |
| $FL$ | Flow rate |
| $GF$ | Ground water table fluctuation |
| $HL$ | Head loss |
| $IA$ | Network instrument age |
| $InD$ | Industrial demand |
| $K$ | Head loss coefficients |
| $K$ | Degree of conflict between two different sources |
| $k_i$ | Steepness of the sigmoid function |
| $L$ | Leakage volume per unit time |
| $L_0$ | Leakage rate for the reference system pressure |
| $L_1$ | System leakage for Pressure $P_1$ and $N1$ is the pressure exponent |
| $lp$ | Number of loops in the network |
| $Ln$ | Lengths of the pipes |
| $LD$ | Traffic loading |
| $LP_N$ | Normalized LP for any condition |
| $LP^{cog}$ | LP for any condition calculated by center of gravity (COG) method |
| $LP_{min}^{cog}$ | Minimum LP for extreme favorable condition calculated by centre of gravity method |
| $LP_{max}^{cog}$ | Maximum LP for extreme unfavorable condition calculated by centre of gravity method |
| $LPRP$ | LP for estimated reference system pressure |
| $LPSP$ | LP for estimated operating system pressure |

| | |
|---|---|
| $N$ | Number of iterations |
| $N1$ | Pressure exponent |
| $ND$ | Nodal demands |
| $NJ$ | Number of joints per kilometer |
| $NM$ | Number of water meters per kilometer |
| $NS$ | Number of service connections per kilometer |
| $P$ | Water Pressure |
| $P_0$ | Reference system pressure |
| $P_1$ | System pressure at any time |
| $p_i(t)$ | Nodal pressure at node $i$ at time $t$ |
| $PA$ | Pipe age |
| $PD$ | Pipe diameter |
| $PP$ | Quality of pipe placement |
| $PM$ | Pipe materials |
| $Q$ | Water quality |
| $q_{l,i}(t)$ | Leakage flow rate at node $i$ at time $t$ |
| $R$ | Roughness coefficients |
| $\tilde{R}$, | Normalized decision matrix |
| $R_f$ | Degree of failure membership |
| $r_s$ | Spearman rank correlation coefficients |
| $R(U, \mu)$ | Reliability expressed in terms of utility and belief |
| $RD$ | Residential demand |
| $RL$ | Reservoir water levels |
| $SP$ | System pressure |
| $ST$ | Soil Type in terms of percentage finer |
| $TF$ | Temperature fluctuation |
| $U$ | Utility gained from a WSS |
| $\tilde{w}_j$ | Fuzzy weight of $j^{th}$ criteria |
| $X_{ij}^k$ | Parameter as child no. i of parent j and generation k |
| $\tilde{x}_{ij}$ | Fuzzy rating of the $i^{th}$ alternative for $j^{th}$ criteria |
| $Y$ | The most likely values of dependent parameters |
| $\hat{Y}$ | Monitored data for a particular time |
| $Y1'$ | Minimum values of dependent parameters |
| $Y2'$ | Maximum values of dependent parameters; |
| $Y'_{12}$ | Both the minimum $(Y'_1)$ and the maximum $(Y'_2)$ values of the dependent variable |
| $Z$ | Elevation head |
| $\sigma$ | Standard deviation |
| $\alpha$ | Orness |
| $\varepsilon$ | Error |
| $\mu$ | Belief on the calculated utility |

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# DEDICATION

*To my mother*

*who showed me how to overcome constraints*

*To my father*

*who showed me how a hard worker is different from others*

*To my sister Salina Akter*

*who gave me her space to grow*

*To my elder brother Mohammad Rafiqul Islam*

*who smiles always inspire me*

*To the memory of my grandmother Koolsom Begum*

*who was my shelter in my childhood*

*To my uncle Ashraf Ali*

*who is my all-time mentor*

*To my aunty Sofia Khatoon*

*who showed me how to dream*

*To my school teacher Hazrat Ali sir*

*who showed me that everyone has a great potential*

*To my uncles Motaher Hossen and Lal Mahmood*

*who are special to me for their supports*

*To my lovely wife Farjana Alam*

*who showed the hidden importance of things and whom I care a lot*

*To my daughter Sarina Islam and son Farasat Shayaan Islam*

*who are the future of my dreams*

# Chapter 1 INTRODUCTION

## 1.1 Background and Motivation

Water supply system (WSS) is the lifeline of a human civilization. A well-maintained WSS is an asset to a community. The idea of a WSS can be traced back as early as 1500BC when the City of Knossos (Minoan civilization) develops an aqueduct system to transport water (Haestad et al. 2003). Roman started constructing a community based WSS (aqueducts) from 312 BC (Ormsbee 2006). In 1652 AD, the City of Boston in the United States first constructed a WSS to supply water for domestic use and fire-fighting. The first piped water distribution was operated in Toronto, Ontario in 1837AD privately (OSWCA 2001).

Although the history of WSS started from a system of few pipes, a modern day WSS consists of raw water sources, raw water transmission pipes, water treatment plants and treated water distribution system. A typical water distribution system (WDS) consists of distribution pipes, nodes (pipe junctions), pumps, valves, storage tanks or reservoirs and different types of service connections for residential, commercial, industrial and agricultural water use. Although in some literature, the "water supply system" and the "water distribution system" have been used interchangeably, in this thesis, these terms have been used for specific purposes. A WDS is a subset of a WSS. A WDS begins at the point of exit of a water treatment plant and ends at the point of use.

From the beginning of water supply history to current day, the main purpose of a WDS is to deliver safe water with desirable quantity, quality, and continuity (pressure) to consumers in a cost effective manner. However, in many cases WDS fails to meet its objective either due to structural and associated hydraulic failure (SHF) or water quality failure (WQF). The SHF causes water losses and interrupts water supply to the consumers with desirable quantity and continuity with desired pressure whereas the WQF may pose a serious threat to consumers' health. A breach in the structural integrity makes the WDS vulnerable for contaminant intrusion and may compromise the water quality as well. Commonly, WDS bears certain structural integrity issues which are manifested by the percentage of non-revenue water (NRW) and the resulting degraded water quality.

The global water supply and sanitation assessment report (WHO-UNICEF-WSSCC 2000) estimated that the typical value of NRW in Africa, Asia, Latin America and Caribbean and in North America are 39%, 42%, 42% and 15%, respectively. According to Frauendorfer and Liemberger (2010), the non-revenue water in Central Asia, West Asia, Middle East, South Asia, and Southeast Asia are 40%, 40%, 25%, 30% 35%, and 35%, respectively. According to Kaj Bärlund, the director of the Environment and Human Settlements Division of the United Nations Economic Commission for Europe, on average between 40 and 60% of treated water is lost in Europe before it reaches to the consumers' tap. The situation is severe in developing countries where the combination of aging / or lack of infrastructure and poor operational practices are common.

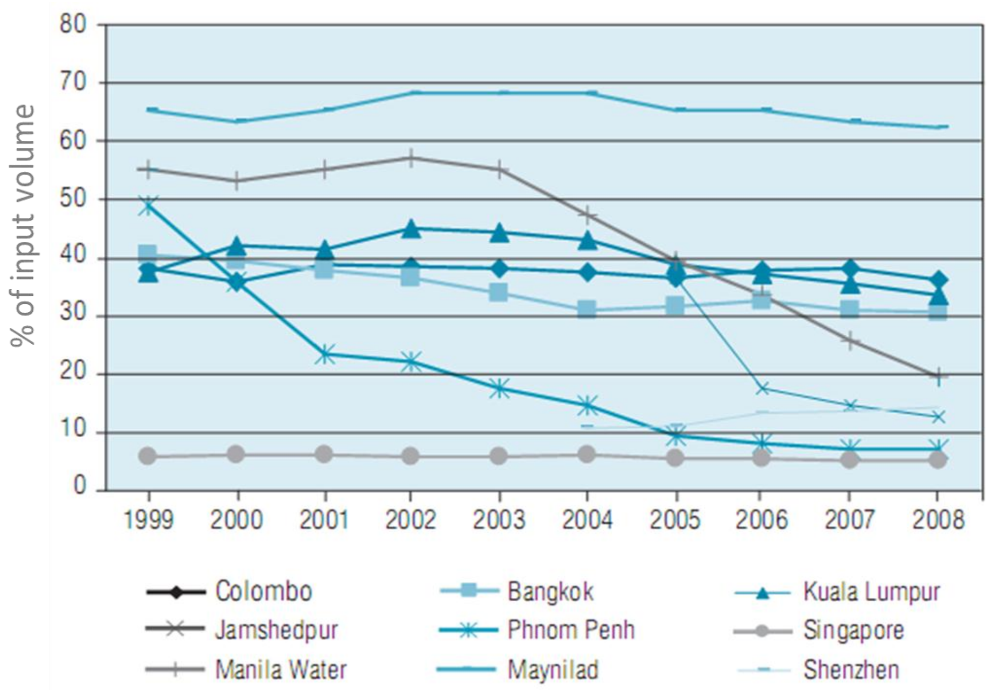


Figure 1.1: NRW in some of the Asian Cities (ADB & IWP 2010)

Figure 1.1 shows non-revenue water in some of the Asian Cities. It is interesting to note that the city of Maynilad, Philippine has a steady NRW more than 60% and most of the other Asian Cities have NRW more than 30%. One of the major component of this NRW is the lost water through leakages (Farley and Trow 2003).

Due to the huge volume of water losses, billions of dollars are lost every year around the world. Water main breaks cost about $1 billion every year in North America (Najjaran et al. 2006). According to a conservative estimate by Kingdom et al. (2006), total cost for water utilities due to NRW worldwide is around US$14 billion/year. The amount of water lost every day through leakage only from the developing countries can serve nearly 200 million people who currently lack access to safe water. Hence, the need to reduce leakage from WDS has gained almost universal acceptance (Howarth 1998).

On the other hand, water quality in WDS warrants maximum attention to ensure a safe drinking water for the consumers. However, the current WDS operation & maintenance (O&M) and management practices do not necessarily address the vulnerability of water to be contaminated (external phenomenon) or deteriorated (internal phenomenon) in the system after the treatment (US EPA 2006). Since 1975, over 200 credible or suspected waterborne events have been recorded in Canada (Health Canada 2002). In year 2000, in Walkerton (Canada), seven deaths and more than 2,300 people were affected by contaminated water and showed the symptoms of gastrointestinal illness due to *E. coli* (Medema et al. 2003; Sadiq et al. 2008). In year 2001, the North Battleford (Saskatchewan) experienced *Cryptosporidium* outbreak affecting approximately 14,000 people. Approximately 5,800-7,100 reported cases of diarrheal illness were linked to this incident (Health Canada 2002).

In addition, hundreds of boil water advisories every day across Canada, and elsewhere highlight the importance of drinking water quality issues. Table 1.1 shows the vignette of national boil water advisories on 24th August, 2011 in Canada (Water 2011). It can be seen that on a typical day in Canada, 50 water purveyors forbid to consume their water at all and ~1200 water purveyors suggest boiling before consumption.

Fortunately, the countries in Europe and North America have much better capabilities to control and manage their water distribution system. The situations in developing countries are worse, but, they have limited capabilities to address water quality issues. In these countries, a significant percentage of the populations do not have access to drinking water and whoever may have access but not guaranteed to have safe water. For example, about 85% of Indian urban population have access to drinking water but only 20% of the available drinking water meets the WHO health and quality guidelines (Khatri and Vairavamoorthy 2007).

Table 1.1: Number of WDS with different types of advisories in a typical day (24th August, 2011) in Canada (Water 2011)

| Province | Red* | Yellow* | Cyan* |
|---|---|---|---|
| Alberta | 1 | 36 | 4 |
| British Columbia | 3 | 274 | 2 |
| Manitoba | 2 | 106 | 0 |
| New Brunswick | 0 | 11 | 3 |
| Newfoundland & Labrador | 1 | 197 | 0 |
| Northwest Territories | 0 | 2 | 0 |
| Nova Scotia | 1 | 70 | 1 |
| Nunavut | 0 | 0 | 0 |
| Ontario | 5 | 115 | 16 |
| Prince Edward Island | 0 | 3 | 0 |
| Quebec | 34 | 138 | 5 |
| Saskatchewan | 3 | 246 | 0 |
| Yukon Territory | 0 | 1 | 0 |
| Total | 50 | 1,199 | 31 |

*A WDS with "red" advisory suggests not to consume water, a "yellow" advisory suggests for boil water or cautionary measure; a "cyan" advisory indicates the effects of cyanobacteria bloom in the system

Hundreds of water quality failure events around the world cost billions of dollars every year. Consumption of non-compliant drinking water may have serious direct and indirect consequences and hence, costs. Direct costs are associated with the loss of revenues due to the interruption of water supply, location and identification of the sources of water quality failure and its remedial action, insurance in case of consumer sickness or death. Indirect cost includes consumers' sickness, their treatment cost, and additional loads of the local hospital, loss of productivity of affected populations and families and so forth. Only the medical and productivity cost of a WQF event is enormous. According to Corso et al. (2003), the estimated total medical and productivity lost costs resulting from *Cryptosporidium* outbreak in Milwaukee, Wisconsin in 2003 were US$31.7 million and US$64.6 million, respectively. In general, a water quality outbreak reduces the consumer confidence in the piped water supply which leads to the reduction of the confidence in the industry in general (Karanis et al. 2007).

A WDS is a spatially distributed infrastructure comprises of hundreds (based on size) of kilometers of buried pipes, joints, intermediate tanks, and consumers' fixtures and fittings. Due to the heterogeneity of different components and their materials, ages, construction quality, the occurrences of multiple physical / chemical / biological processes over the time, and the lack of timely data, it is difficult to fully understand the deterioration of different components of a WDS and water quality changes within the system before delivered to the consumers. Therefore, a failure (either SHF or WQF or both) can happen any time and at any point without being understood and /or noticed. In addition, being a pressurized and a continuous flow system, a change or a failure (i.e., pipe breakage, contaminant intrusion) at a single point may affect the entire WDS or a significant part of the system. There are numerous reasons that may change the system or cause failure. Rapidly increasing urban sprawl, aging of water distribution infrastructure and poor O&M practices, deterioration of source water quality, and management practices have significant impacts on the system failure (Charron et al. 2004). In USA, since 1940, up to 40% of reported waterborne disease outbreaks have been linked to the WDS problems (US EPA 2006). Accidental intrusion or malicious activities may also contribute to water quality failure in a WDS. In addition, various distressing factors such as ageing of the infrastructure, operational conditions, increasing demand, climate change, and sudden shocks can lead to the WDS failures (both SHF &WQF) and may cause critical consequences on the community sustainability in terms of public health & safety especially, related socioeconomic and environmental costs.

Whatever might be the reason for the failure, both likelihood and the consequence of the failure can be reduced to an acceptable limit if the prognostic analysis and necessary preventive measures are taken on time. In case of failure, consequence of the failure can be reduced significantly if the occurrence of failure is detected and necessary actions are taken in a minimal time after its occurrence. Therefore, interventions are necessary to reduce the likelihood and consequence. The interventions could be for day-to-day O&M activities such as failure detection, location and repair or for long-term improvement, rehabilitation and replacement. Therefore, utility managers require tools for an informed interventions and a better decision making.

Numerous studies on a WDS failure investigation and asset prioritization for the long-term improvement have been reported in the literature (Alegre 1999; Allen et al. 2004; Besner et al. 2001; Engelhardt et al. 2000; Farley 2001; Francisque et al. 2009; Li 2007; Poulakis et al. 2003; Sadiq et al. 2010; Storey et al. 2010). Due to the associated uncertainties resulting from the WDS complexity, the methodologies developed in these studies were not fully capable to solve the problems faced by utility managers. Although the related literature acknowledged the high levels of uncertainties, most of them did not address the uncertainties in the analyses, and even when incorporated, uncertainties were poorly addressed. Therefore, in many cases, the asset prioritization models prioritize wrong assets which do not require intervention at a given point of time. In a similar fashion, during the failure diagnosis, these models either produce many cost-incurring false positive alarms of failure or fail to detect the actual failure events by generating false negative alarms. Most of the studies have limited capability and attempted to address individual issues in a WDS. In this research a more efficient and decision framework has been developed which addresses the uncertainties in an integrated manner that can provide better confidence in the prognostic and diagnostic investigations. The developed framework will guide long-term improvement in the WDS management and will help in day-to day-operation and maintenance (O&M) such as failure detection, location and repair/ replacement.

## 1.2 Research Objectives

The main goal of this research is to develop an integrated decision support system framework for prognostic and diagnostic analyses of WDS failures. The interventions based on the prognostic analysis will reduce the likelihood of failures, and in case of a failure, the diagnostic analysis will minimize the consequences of the failure. The objective has been achieved by developing an integrated decision support system framework for prognosis and diagnosis analysis.

The specific objectives of this research are to:

1. develop a reliability assessment model for evaluating WDS performance/ serviceability as a tool for prognostic investigation
2. model leakage "potential" in a water distribution system to evaluate the structural integrity of the system as a tool for prognostic investigation
3. detect and locate actual leakage in a water distribution system as a tool for diagnostic investigation
4. model water quality failure "potential" in a water distribution system to evaluate water quality as a tool for prognostic investigation
5. detect and locate "actual" water quality failure in a water distribution system as a tool for diagnostic investigation
6. integrate the developed prognostic and diagnostic models at a common platform and develop a proof-of-concept decision support system for WDS management, and
7. demonstrate the proof-of-concept of the different developed models using case studies.

First five objectives have been achieved by developing a set of five models which are standalone but are integral part of developed decision support system. The sixth objective is achieved by developing an integrated decision support system which encompasses the inputs and outputs of the developed models and other external information. The final objective is a part of first six objectives and has been achieved through selecting different case studies to demonstrate a proof-of-concept of developed models.

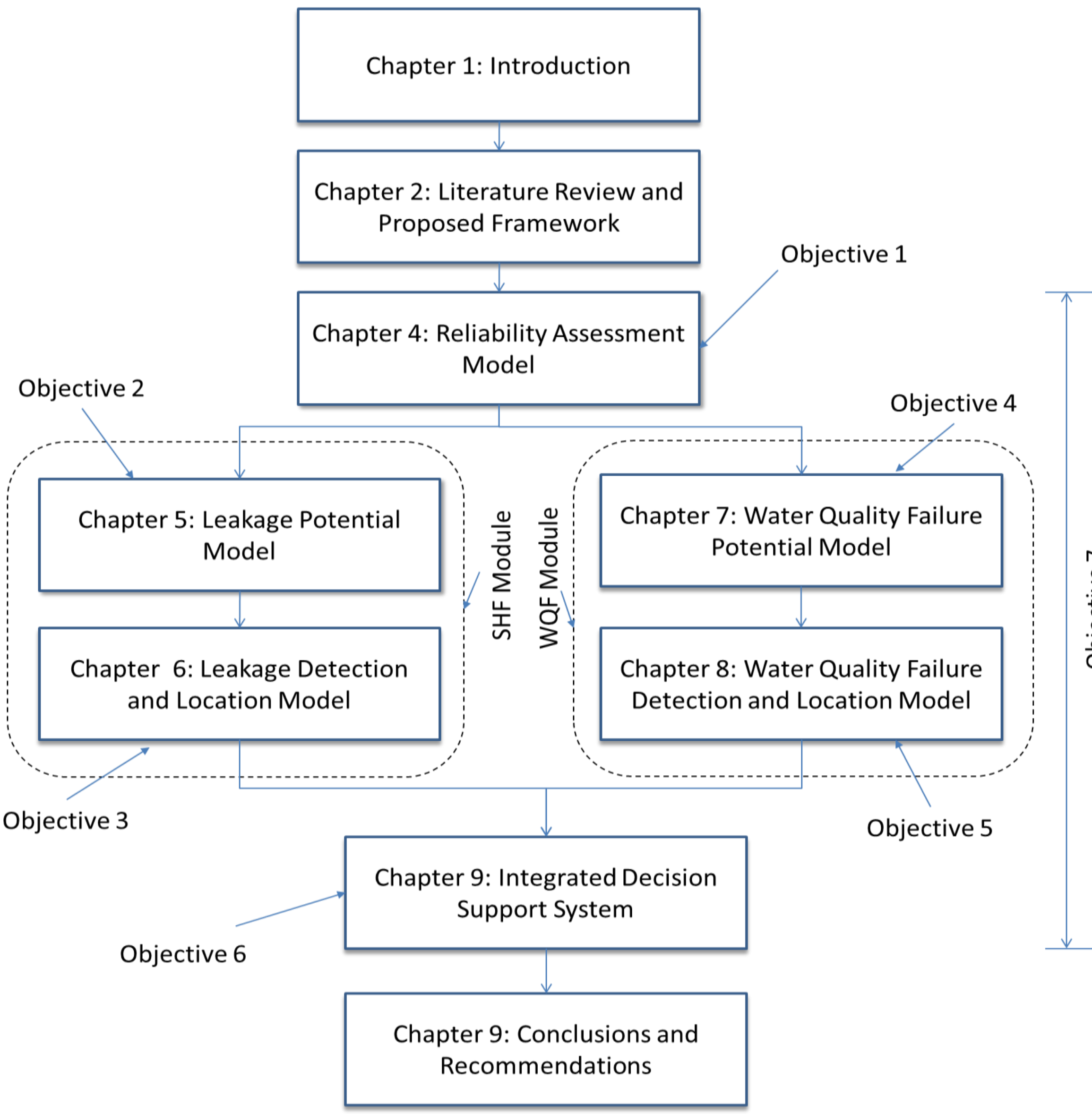


Figure 1.2: Thesis structure and organization

## 1.3 Thesis Organization

This thesis contains nine chapters. Following the introductory chapter, Chapter 2 reviews the literature relevant to this study and proposes a framework for WDS failure prognosis and diagnosis analysis. As a part of an integrated decision support system, Chapter 3 to Chapter 7 provides details for the development and standalone applications of five individual models. Chapter 8 provides the process of integration whereas Chapter 9 summarizes research outcomes and provides recommendations for future research. The organization of the thesis has been shown in Figure 1.2.

# CHAPTER 2 LITERATURE REVIEW AND PROPOSED FRAMEWORK

A version of this chapter has been submitted for publication to *The special issue of the Tunnelling and Underground Space Technology (TUST) incorporating Trenchless Technology Research* with the title “Water Distribution System Failure: A Forensic Analysis” ( Islam et al. 2011a). This paper is under second review.

This chapter consists of two parts. The first part provides a brief review of literature related to this research and identifies drawbacks and limitations of existing studies. In the second part, a framework for WDS failure prognostic and diagnostic investigations has been proposed.

## 2.1 Literature Review

This section introduces the basic definitions in the context of WDS modelling, common tools for WDS modelling, multicriteria decision analysis techniques, uncertainty analyses and provides a review of literature related to the structural and associated hydraulic failure and water quality failure. The review provided in this section is general in nature. However, model related problem specific literature reviews have been included in subsequent model development chapters. For example, literature review relevant to the reliability assessment has been provided in Chapter 3 and so forth.

### 2.1.1 Basic Definitions in the Context of WDS Modelling

**Failure Potential**: The term ‘potential’ for failure has been used to refer to the ‘possibility’ or ‘likelihood’ of failure. The scale of ‘potential’ is defined as a continuous interval of [0 1] or [0 100%]. The term ‘possibility’ or ‘likelihood’ refers to *what can happen* whereas ‘probability’ refers to *what will happen* (Sadiq et al. 2010). But the essence of the term ‘potential’ is very similar to the ‘possibility’ or ‘likelihood’. A 100% leakage potential of a WDS means that the production volume and leakage potential are same in that WDS. An effective 100% leakage potential in a WDS refers to the condition that the water cannot be transported to the tap of a consumer. Similarly, an effective 100% WQF potential in a WDS refers that the water from the system is totally unacceptable to drink.

**Reliability**: The term “reliability” is defined as the probability that a system will perform its intended function for a given period of time under a given set of condition (Lewis 1987). It is a complement of probability of system failure. A reliable WDS ensures adequate quantity, quality and continuity (enough pressure) of water supply under normal operating condition, and during the emergency loading condition, the water quantity, quality, and pressure must not go below the predefined level of service (Zhao et al. 2010). In this research, the concept of reliability has been investigated from hydraulic and water quality failures view point.

**Risk**: The term “risk” is defined as a product of likelihood of an undesirable event (i.e., the likelihood of occurrence of the event), and its related consequences (Sadiq et al. 2004). Rowe (1977) has defined the risk as *the potential for realization of unwanted, negative consequences of an event*. In this study, the risk refers to the product of likelihood of WDS failure to supply water to the consumers under a predefined level of service for quality, quality and continuity (pressure) and their consequences.

**Utility and Disutility**: According to the Oxford English Dictionary, the term “utility” means the fact, character, or quality of being useful or serviceable. In this study, the term “utility” refers to the quality of being serviceable of WDS to fulfill the consumer desire to get safe water with desirable quality, quantity and continuity. The utility function, U (X) has been defined as a function of available and expected water quality, quantity, and pressure. The term disutility, DU (X) has been used as a complement of a utility as follows:

$$DU(X) = 1 - U(X) \qquad [2.1]$$

### 2.1.2 Risk-based WDS Modelling

Although the history of risk-based WDS management is not very old (Egerton 1996), a significant number of studies on risk-based WDS management have been reported in the literature. In the recent times, the modelling of WDS has shifted towards more to the risk-based analysis. The term “risk” has the capability to encompass non-commensurate inputs into a single entity defined by the product of likelihood and consequences. This special characteristic makes risk-based analysis an attractive alternative for water distribution system modelling (Sadiq et al. 2009). In the risk based WDS modelling, generally, likelihoods or risks of all the WDS components are evaluated against the potential causes of failure. Risk maps are most common to visualize the likelihood/ risk of individual component (Bicik 2010). From a risk map, a decision maker can make an informed decision to take /

prioritize any action to the relevant component of the WDS. An aggregated risk can provide overall condition of the system rather relative importance of the different component of the WDS. Pollard et al. (2004) provides a review of risk analysis tools and techniques, risk-based methodologies and their applications for the strategic, program and operational levels of decision-making. Table 2.1 provides a summary of common risk-based WDS modelling applications and their key attributes.

Table 2.1: Application of risk-based water distribution modelling

| Reference | Model Type | Model output | Parameters/ Inputs/data | Risk Type |
|---|---|---|---|---|
| Besner et al. 2001; Bicik 2010 | DSS model based on hydraulic model coupled with GIS, Evidential reasoning | Risk maps | Failure data, hydraulic parameters (pipe diameter, length, roughness coefficient and so forth) | Water losses |
| Li 2007 | Hydraulic and quality | Aggregative risk | Hydraulic and water quality parameters | Reliability, health and public safety |
| Fares and Zayed 2009 | Fuzzy-based expert system | Aggregative risk | Hydraulic and water quality parameters | Reliability- based |
| Vairavamoorthy et al. 2007 | Fuzzy logic, GIS | Intrusion susceptibility | Contaminant source, concentration and pipe condition ( pathways) | Reliability-based |
| Sadiq et al. 2007; 2004 | Fuzzy logic | Aggregative risk | Various water quality failure mechanism in water distribution system | Reliability-based |
| Howard et al. 2005 | Point scoring method, GIS | Risk maps | Hydraulic parameters, soil corrosions, sources of contaminants, population at risk | Health and public safety |
| Makropoulos and Butler 2004; 2005; 2006 | GIS, Fuzzy logic | Risk maps | Soil corrosivity, pipe attributes (age, diameters, materials), location sensitivity | Reliability-based; health and public safety |
| Mamlook and Al-Jayyousi 2003 | Fuzzy logic | Leakage detection | Hydraulic parameters | Reliability-based |

Adapted from Sadiq et al. 2009; DSS= Decision Support System; GIS= Geographical information System

In the literature most of the risk based WDS modellings have been used to either to prioritize the pipe renewal plan or to prioritize different WDS system management options. However, their application for day to day operation is very limited. In this research risk based approach has been used for asset prioritization as well as day to day operation such as failure detection and location.

### 2.1.3 Common Tools for WDS Modelling

Modelling of WDS is a key tool evaluating current hydraulic and water quality condition of a WDS as well as an analysis of future scenarios for planning and design of a WDS. Generally, a computer program is used to predict water pressure, flow, and water quality parameters within the distribution system to evaluate a design and to evaluate the performance of WDS against predefined criteria. The computer program solves a set of energy, continuity, transport, or optimization equations to estimate pressure, flow, and water quality parameters (AWWA 2005). Numerous commercial software are also available in the market. Most of the commercial software have advanced graphical interfaces, GIS tool and capability to integrate with advanced database management system. Table 2.2 shows a summary of the key features of leading available WDS modelling software.

Table 2.2: Key features of different WDS modelling software

| Properties | E | A[1] | S[1] | W[1] | H[1] | K |
|---|---|---|---|---|---|---|
| Hydraulic simulation (steady and dynamic) | • | • | • | • | • | • |
| Surge modelling | | • | | | • | • |
| Water quality simulation (steady and dynamic) | • | • | • | • | • | • |
| Multi-species interaction | • | • | • | | • | |
| Extended period simulation | • | • | • | • | • | • |
| Pump optimization | | • | • | • | • | • |
| Leakage control zone handling | | • | • | • | • | • |
| Automatic model calibration | | • | • | • | • | • |
| Area isolation modelling | | • | • | • | • | • |
| ODBC driver for all input / output | | • | | • | • | • |
| Scheduler, real-time, and forecaster module | | • | • | • | • | • |
| Interface to GIS / CIS/ MIS | | • | • | • | • | • |
| Public domain software | • | | | | | |
| Open source code for modification | • | | | | | |

E=EPANET/ EPANET-MSX; A= AQUIS; S=Stoner SynerGEE; W= WaterCAD; H= H2ONET; K= KYPIPE; ODBC= Open Database Connectivity; GIS= Geographic Information System; CIS= Customer Information system; MIS= Management Information System.

The USEPA developed software, EPANET (Rossman 2000) has wide acceptance among the modelers for its publicly available source code and being a standalone program. In fact, some of the commercially available software (such as MIKE NET) employ EPANET engine for simulation. To execute the proposed framework at the network level, EPANET, its extension, EPANET-MSX

[1] Information collected *via* personal communication

(Shang et al. 2007) and their source codes have been used in this study. The EPANET and its source code have been used for hydraulic simulation, whereas EPANET-MSX source code has been used for multi species water quality simulation. Details of hydraulic and MSX model development have been provided in Chapter 7. EPANET performs extended period simulation of hydraulic and water quality behavior within the pressurized pipe network consisting of pipes, nodes or junctions, pumps, valves, and storage tanks or reservoirs. The model computes junction heads and link flows for a fixed set of reservoir levels, tank levels, and water demands over a succession of points in time (Rossman 2000).

### 2.1.4 Multicriteria Decision Analysis (MCDA) Techniques

Multicriteria decision analysis (MCDA) techniques represent a set of techniques potentially capable of improving the transparency, auditability, and analytic rigors of various decisions (Dunning et al. 2000) by formulating the problem by a finite number of alternatives, and a family of performance measures arising from different perspectives (Kodikara 2008).

Table 2.3: Key MCDA Techniques

| MCDA Category | MCDA Techniques | References |
|---|---|---|
| Multicriteria value functions | Multi-attribute utility theory (MAUT) | Keeney and Raiffa 1976 |
| Pairwise comparison | Analytic Network Process (ANP); Analytical Hierarchy Process (AHP) | Saaty 1980; 2005 |
| Distance to ideal point | Technique for Order-Preference by Similarity to Ideal Solution(TOPSIS) | Hwang and Yoon 1981 |
| Outranking approach | Preference Ranking OrganizationMETHod for Enrichment Evaluations(PROMETHEE); ELimination Et Choix Traduisant la Realite(ELECTRE) | Brans et al. 1986; Roy 1968 |
| Aggregation | Ordered Weighted Averaging (OWA) | Yager 1988 |
| Preference intensities | Simple Multi-Attribute Rating Technique (SMART) | Von Winterfeldt and Edwards 1986 |
| Utility function | Utility Theory Additive (UTA) | Jacquet-Lagreze and Siskos 1982 |

Generally, an MCDA technique is represented by an evaluation matrix $\boldsymbol{X}$ of $n$ decision options, and $m$ criteria ($n \geq 2$ and $m \geq 2$) where the rows of the matrix are performance scores for decision options $i$ with respect to criteria $j$ are denoted by $x_{i,j}$. For MCDA, numerous techniques have been documented in the literature. A summary of common techniques used for the water supply arena has been summarized in Table 2.3. In this study two MCDA techniques TOPSIS (Hwang & Yoon 1981), abbreviated from *Technique for order preference by similarity to ideal solution* and Order weighted averaging (OWA) (Yager 1988) have been investigated in Chapter 6.

### 2.1.5 Uncertainty in WDS Modelling

Modelling of WDS requires information for various inputs parameters from various sources. These input parameters can be classified as hydraulic parameters such as nodal demands, pipe diameters, pipe roughness coefficients, and water quality parameters such as global bulk, and wall decay coefficients.

Table 2.4: Sources of uncertainty in water distribution system modelling

| Sources | Causes of Uncertainty | Type of Uncertainty |
|---|---|---|
| Skeletonisation | • Exclusion of pipes (i.e., small pipe, newly developed network)<br>• Reduction of pipe segments (similar pipes in series are modelled as single pipe)<br>• Reduction of pipe numbers (multiple pipes in parallel are modelled as a single pipe using hydraulic equivalence) | Epistemic |
| Demand | • Natural temporal variability of demand (aleatory)<br>• Incorporation of demand pattern (epistemic) | Aleatory and epistemic |
| Pipe and roughness | • Roughness<br>• Effective diameter (deposition inside the pipe wall) | Epistemic |
| Reservoir levels | • Variability of reservoir level | Epistemic |
| Pumps and valves | • Pump curve approximation<br>• Exclusion of different minor loss during modelling) | Epistemic |
| Water quality | • Exclusion of dispersion terms<br>• Complete and instantaneous mixing at network junctions<br>• Hydraulic parameter uncertainty<br>• Assumptions on incorrect decay<br>• Reaction with pipe materials | Epistemic |

Due to the nature of different parameters, uncertainties are inherent in their estimation. These uncertainties arise due to lack of complete knowledge of different parameters (epistemic uncertainty) or due to the randomness of parameters (aleatory uncertainty). Table 2.4 shows the key sources of uncertainties encountered in WDS modelling. The uncertainties involved in input parameters propagate throughout the model and ultimately to the model output (Pasha and Lansey 2011). In spite of continuous efforts for better understanding and modelling of uncertainties in WDS, uncertainties (Table 2.4) remain inherent in WDS modelling. Therefore the model loses its capacity to mimic the real situation which hinder prediction WDS failures and in case of failure, detection and location of failures. In this research, significant efforts have been given for better modelling of uncertainties in WDS using various tools and techniques. In literature, a range of techniques has been developed for quantification and propagation of uncertainties in parameters. Table 2.5 shows the key techniques and their basic features reported in the literature.

Table 2.5: Common techniques used for uncertainty quantification and propagation

| Techniques | Key Features | Types |
|---|---|---|
| Probability theory | • Probability is the measure of how likely an event is | Statistical |
| Genetic algorithms | • Generate solutions to optimize problems inspired by natural evolution<br>• Reduction of parameter uncertainty<br>• No quantification of uncertainty | Optimization-based |
| Monte Carlo simulation | • Parameters are randomly drawn from the prior distributions<br>• Uncertainty quantification | Random sampling |
| Bayesian theory | • Combine prior knowledge to a new estimate | Probability-based |
| Evidential theory | • Handle conflicts, randomness, and vagueness | |
| Possibility theory | • Uncertainty is represented by using a possibility function | |
| Fuzzy set theory | • Parameters are expressed with certain degree of membership | Fuzzy based |
| Latin hypercube sampling (LHS) | • Stratified sampling without replacement | Statistical |
| First-order second-moment (FOSM) | • Estimate Parameter uncertainty | Based on Taylor series expansion |

Although various techniques are available in the literature to model uncertainties involved in WDS, fuzzy set theory has been used in this study. Different WDS parameters such as roughness, consumer demand involved in modelling are very imprecise because of their nature and very difficult or nearly impossible to estimate their values with certainty. To address the subjectivity, vagueness, and impreciseness of different WDS parameters fuzzy set theory has been used. Fuzzy set is an object class with a continuum of grades of membership ranging from zero to one characterized by membership function. Fuzzy set is used to deal with vague and imprecise information (Zadeh 1965). It is widely applied to solve real-life problems that are subjective, vague, and imprecise in nature

(Smithson and Verkuilen 2006; Yang and Xu 2002). It provides a strict mathematical framework in which vague conceptual phenomena can be studied precisely and rigorously (Zimmermann 2001). Details of the Fuzzy set theory have been discussed in Chapter 4. However, integrated decision support system has been developed based on the Dempster-Shafer (D-S) theory. Dempster-Shafer (D-S) theory is evidence based mathematical theory. The theory was introduced by Dempster (1967) and extended by Shafer (1976). Since its conceptualization, D-S theory has been used in various engineering applications including water related applications. Details of the D-S theory have been discussed in Chapter 8.

#### 2.1.6 Water Distribution System Failure

In this study, failures of WDS have been classified into two groups-structural and associated hydraulic failures (SHF) and water quality failures (WQF). The structural and associated hydraulic failures (SHF) refers to the failure of transmission and distribution pipes due to various distressing factors which causes damage of transmission and distribution pipes and allow treated water unexpectedly escape from the WDS. The WQF refers to the compromise of water quality resulting from the presences of undesirable contents in water.

The loss of structural integrity or structural failure manifests through the leakage from WDS. Farley and Trow (2003) discussed different leakage pathways, mechanisms of leakage formulation, and relationship of pressure with leakage. They also suggested numerous techniques for leakage estimation and management options. Lambert (2001) showed the relationship of leakage with the operating system pressure. He developed the burst and background estimate (BABE) - a component based leakage volume estimation methodology. However, these authors have not studied the *likelihood* of occurrence (potential) of leakage or LP in WDSs.

Fares and Zayed (2009) studied *risk* for failure of the whole distribution system using fuzzy-based approach. They presented a methodology to evaluate the risk of water main failure using hierarchical fuzzy expert system. However, they did not include small leakage like background leakage in their analysis. Kleiner et al. (2004) proposed a new approach to model the deterioration process of buried pipes using fuzzy-rule-based non-homogeneous Markov process. Their proposed model can yield failure risk as a function of pipe age at every point along the life of the pipe. Jowitt and Xu (1993) presented a methodology for predicting pipe failure effects in WDS without any network analysis.

This methodology provides a technique for estimating the impacts of component failures on overall network and individual nodal performance by assessing the vulnerability of the network to the loss of any particular pipe element. Rogers and Grigg (2006) developed a pipe failure assessment tool to prioritize pipe replacement in water distribution system based on existing pipe inventory and break data from existing records of the utility organization. However, they did not study leakage potential for the distribution system. Mamlook and Al-Jayyousi (2003) proposed a technique to detect leakage in WDS using fuzzy synthetic evaluation. They identified four major factors that affect the leakage: pipe age, pipe material, operational aspects, and demand patterns. They proposed leakage potential in pipes through fuzzy numbers that include 'leakage', 'possible leakage' and 'no leakage'. Based on the first order reliability method (FORM), Yamini and Lence (2009) presented a methodology for estimating the probability of mechanical failure of WDS due to internal and external corrosion. They have shown how the internal and external corrosion affect the service age of the cast iron pipes. Torres et al. (2009) proposed a methodology for vulnerability classification of WDS and applied their methodology to a virtual WDS. Farley et al. (2010) presented a complete enumeration-based methodology to identify the 'optimal' locations of pressure sensors for the detection of a leak/burst. The methodology has been verified by creating an artificial leakage scenario.

Perez et al. (2009) presented a sensor placement and leakage detection methodology to identify (locate) leakage in a WDS based on the deviation of sensor pressure from estimated pressure. They expressed the effect of leakage on the pressure at a node using a sensitivity matrix (Pudar and Liggett 1992). However, they fully acknowledged the difficulty in calculating the analytical values for the sensitivity matrix. Poulakis et al. (2003) proposed a leakage detection methodology based on Bayesian identification. Their methodology was able to estimate the most likely volume and the location of leakage, as well as uncertainties in the estimates. They also addressed the issues related to modelling errors, measurement noise, leakage severity and sensor configuration. However, they acknowledged that this methodology was applicable only to a certain threshold of leakage amount.

Mounce et al. (2010) provided an assessment of the online application and the resulting benefits of an artificial intelligence system for leakage detection. Mounce et al. (2003) presented a methodology based on an artificial neural network (ANN) to synthesize data obtained from different sensors to classify different types of leakage in a WDS. They developed an ANN-based empirical model for the prediction and classification of leakage, using sensor time series data. Because of the ANN-based methodology, this study requires a large monitoring database.

Zhang et al. (2009) proposed a methodology for detecting pipe bursts in a WDS. Their system detects bursts based on their characteristic values and similarity analysis. In their methodology, the system calculates both the ideal burst characteristic values based on the leakage rate, and then estimates the real values. By using the fuzzy similarity ratio of ideal and real values, their system can detect the presence of a burst in a WDS. The reported accuracy of their system was higher than 80%. Misiunas et al. (2005) developed an algorithm by combining continuous monitoring of pressure and hydraulic transient for the detection and identification of location for sudden bursts in a WDS. To identify the location of burst, they used the arrival times and magnitudes of burst-induced transient waves at two or more points. Wu and Sage (2007) proposed an optimization (genetic algorithm) - based methodology to detect leakage in WDS. In their methodology, leakage is considered as a pressure dependent demand, and the difference between the monitored and the model-predicted flow and pressure has been minimized. Aksela et al. (2009) presented a methodology for leakage detection in terms of leakage function based on the self-organizing map using water flow data. There are many other related studies (e.g., Covas et al. 2005; Webb et al. 2009) that highlight the importance of continuing research for better understanding and controlling structural and associated hydraulic failures.

Similar to the literature related to the structural and associate hydraulic failure, a wealth of literature is available on the WQF in distribution system as well. Sadiq et al. (2003) presented a conceptual outline for forensic analysis of WQF in distribution systems. Same authors (Sadiq et al. 2006a) proposed a risk-based methodology for predicting risk of contaminant intrusion in WDS. In the first paper of a series of three paper publications, Sadiq et al. (2010) proposed a framework for modelling the potential for WQF in distribution systems. The main objective of their work was to identify the major deterioration mechanisms which contribute to the WQF, and to develop a deterioration based water quality failure potential model. It is yet to know the impacts of the operating conditions such as pressure, water velocity, etc. on their overall WQF potential. Boxall and Saul (2005) presented a novel cohesive transport modelling approach to simulate the discoloration within WDS.

Storey et al. (2010) provides a review of drinking water quality monitoring technologies adapted in different part of the world. Based on the review, the reviewers agree with the Global Water Research Coalition (GWRC) and United States Environment Protection Agency (USEPA) that in spite of many emerging technologies, a significant research improvement is necessary to deploy those emerging technologies to the existing operations. Westrell et al. (2003) examine influences of water quality failure, especially microbial (*Cryptosporidium parvum*, rotavirus and the bacterium *Campylobacter jejuni*), on the annual risk of infection of the population served. Richardson et al. (2009) shows environmental and climatic impacts on water quality based on the passive surveillance in the private water supply system in England. From the analysis, they found very strong seasonal influences on water quality in a private water supply system. Lindhe et al. (2009) developed an integrated and probabilistic risk analysis method for WDS using fault analysis. The authors evaluated consumer minutes lost as a measure of risk resulting from the water quantity and quality failure. Rizak and Hrudey (2008) provide a review and analysis of different published papers to identify the common risk factors related to weather and water treatment process which contributes to th drinking-water disease outbreaks.

Although a huge volume of research on structural, hydraulic and water quality failure has been reported in the literature, a holistic view of different kinds of failure investigation is not reported in the literature. In the literature, different kinds of failure have been treated an individual incidence and modelled as individual type of failure. In reality, different kinds of failures are linked with similar/ same WDS parameters. As a result, when one kind of failure occurred in a WDS system, it also influences the other type failure. It is also reveal that the most of the models have been employed in strategic applications rather for operational problems. A limited number of research has been reported to address the operational issues related a WDS such as instantaneous failure potential evaluation and in case of failure, detection and location the failures. Available fragmented prognostic and diagnostic literature either produced many unreliable predictions incurring extra cost for utility operation.

## 2.2 Proposed Framework

To address the different limitations highlighted previously an integrated framework has been proposed for better prognostic analysis and diagnostic investigation of WDS failures. Figure 2.1 shows the proposed framework and interrelationship of different objectives of this research. The proposed framework has analogy to the operation and diagnosis process of an Accident and Emergency (A&E) in a hospital. Table 2.6 provides a comparison of A&E operation and diagnosis, and proposed framework.

In a hospital, patients are evaluated by a nurse on arrival to prioritize the level of emergency and to identify the potential group of diseases. This helps to direct the patients to relevant physicians. If a patient's condition is severe, the patient might be transferred to the operation theatre for surgery, if deemed. Similar assessment will be conducted for WDS by assessing the reliability of WDS in terms of utility.

**Table 2.6:** Comparison of accident and emergency (A&E) and proposed framework

| Step | A&E Operation and Diagnosis | Proposed WDS Framework |
|---|---|---|
| 1 | • On arrival: patient evaluation and disease classification.<br>• Based on evaluation results, the patient might be transferred to the specialized unit. | • Reliability assessment in terms of utility of the WDS. A risk assessment will be conducted based on the extents of reliability issues to prioritize long-term risk management action.<br>• For operational issues further investigation |
| 2 | • Evaluation for the potential for each group of diseases | • Evaluation of potential for SHF and WQF |
| 3 | • Identification of diseases and prescription | • Identification of leakage location, water quality failure location and cause of the failure |

Based on the reliability assessment, water managers will decide whether a short term or long term reliability issue exists in the system which requires attention. If the reliability is compromised due to operational issues, the decision makers can further perform diagnostic investigation and take necessary operational interventions. To address the operational issues, the utility managers will identify the types of failures whether the failure is due to the structural and associated hydraulic problem or due to the water quality problem. Based on the nature of the operational issues, the proposed framework will deal with two types of failures, namely, structural and associated hydraulic failures and water quality failures.

In the second step, in an A&E of a hospital, the relevant group of physicians will evaluate the potentials for different kind of diseases based on the diffident symptoms, patient history, and recent activities of the patient. In case of proposed framework, similar analysis will be carried out by prognostic investigation of WDS such as evaluating potentials for SHF and WQF.

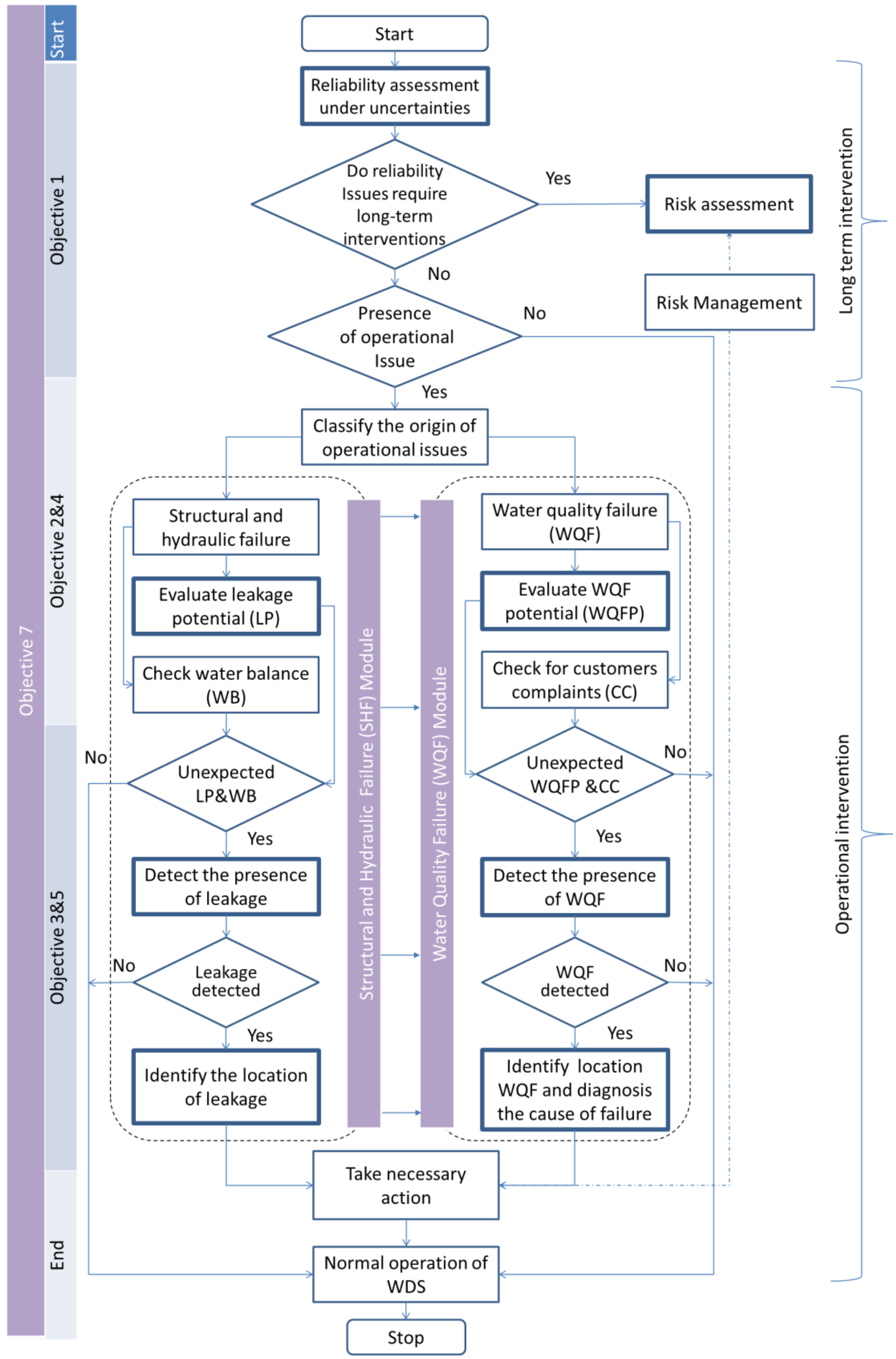


Figure 2.1: Flow chart of the proposed framework (Bold outlined blocks relate to major objectives)

The potential for SHF can be estimated in terms of leakage potential. Leakage potential and water balance (Farley and Trow 2003) results will be checked to confirm the structural integrity of the system. If either unexpected leakage potential or unexpected water balance or both are observed, the WDS will be evaluated in the third step. However, if neither unexpected leakage potential nor unexpected water balance is observed, then hydraulically WDS will be in normal condition. In a similar way, for water quality failure, the water quality failure potential, regular laboratory test results and consumer complaints database will be investigated for further information on water quality failure and take necessary action as required.

In the third step, in hospital, the physicians diagnose the disease and prescribe appropriate medication to the patient. For the WDS, utility managers will identify the presence of failure (SHF & WQF; if any). After identification of the failure, the utility managers will highlight the most probable locations of failure (either SHF or WQF). In case of WQF, the utility managers will identify the most probable reason for the failure as well.

The proposed framework has been implemented using five new models based on five novel methodologies developed during this research. The following sections provide a brief summary of the developed models for the proposed framework. Details of all the models have been discussed in relevant chapters of this thesis. The proposed framework is executed based on different inputs and outputs of these developed models which has been described and demonstrated in Chapter 8.

### 2.2.1 Reliability Assessment Model

This model has been developed using a novel reliability assessment methodology (Chapter 3) based on consumers' utility (satisfaction) received from a WSS in terms of water pressure, available water volume and quality of available water. The proposed methodology is based on two components, namely, the utility received by consumer and associated belief of calculated utilities which also quantifies the effects of uncertainties of WSS independent parameters on the estimated utility. For the development of overall reliability, it is necessary to evaluate hydraulic and water quality utility and their corresponding beliefs. Besides the measure of reliability and the associated uncertainties, the hydraulic and water quality utility also help for evaluating overall state of water distribution system and, in case of failure, identify the most probable location of failures.

### 2.2.2 Leakage Potential Model

This model has been developed (Chapter 4) as a part of the prognostic investigation for structural and associated hydraulic failure (Chapter 8). The study has identified various factors which are directly and/or indirectly influence the leakage in WDS. Considering various leakage influencing factors, developed model estimates the leakage potential in WDS. To aggregate the influence of each factor, a fuzzy rule-based model has been developed. To model the behavior of different influencing factors under varying operating system pressure, a pressure adjustment factor has been developed and incorporated with the aggregation process.

### 2.2.3 Leakage Detection and Location Model

This model has been developed (Chapter 5) as a part of diagnostic investigation for structural and associated hydraulic failure (Chapter 8). Using the hydraulic model and sensor data, the model can identify the presence of an "actual" leakage, if any, and highlights the most probable leaky node and/or leaky pipe. The model requires identification and fuzzification of different independent WDS parameters such as roughness coefficients, nodal demands, and water reservoir levels and three sets of network solutions. Based on fuzzy independent parameters, using the EPANET simulation engine, fuzzy depended parameters, such as nodal pressure and pipe flow, are estimated. Dependent parameters, pressure and flow data obtained from sensors have been compared with estimated fuzzy dependent parameters. From the comparison, presence of leakage and its location has been identified.

### 2.2.4 WQF Potential Model

This model has been developed as part of a prognostic investigation (Chapter 8) for water quality failure in WDS. The developed model evaluates water quality failure potential in WDS. Different water quality influencing parameters have been identified and divided into two categories: the *symptoms* of WQF such as taste and odor, and the *causes* of WQF such as free residual chlorine and ammonia. A causal relationship of the *symptoms* and the *causes* of WQF have been developed. Based on the developed relationship, a fuzzy –TOPSIS –OWA-based model has been developed to evaluate water quality failure potential. To address the subjectivity of the impacts of different parameters (both in the *causes* and the *symptoms*) fuzzy set theory has been used.

The TOPSIS has been used to evaluate the influences of different WQF causal parameters for WQF potential. In TOPSIS, alternatives are compared with the positive and negative ideal solutions. The basic philosophy of this technique is to choose alternative closest to the positive ideal solution and farthest from the negative ideal solution. Finally, to aggregate the impacts of the different parameters OWA operator has been used. To include the decision maker's attitude in the aggregation process, Yager (1988) introduced the order weighted averaging (OWA) operator as a form of general mean type operator. The OWA operator provides flexibility to utilize the range of "*anding*" or *"oring"* which helps to include the decision maker's attitude in the aggregation process (Sadiq et al. 2010).

### 2.2.5 WQF Detection and Diagnosis Model

This model is an extension of WQF potential model and important part of diagnostic investigation of water quality failure. This extended part of the model detects the presence of water quality anomaly, if any, and evaluate the influences of different water quality parameters from which identifies the most probable *cause* of WQF. After the contamination detection, it highlights the most probable origin and ingress rate of the identified WQF event and finally, identifies the most severely affected node in the WDS.

# CHAPTER 3 RELIABILITY ASSESSMENT MODEL

A version of this chapter has been submitted for publication to *ASCE Journal of Water Resource Planning and Management* on 11$^{th}$ March 2012 with the title "Reliability Assessment for Water Supply Systems: A Novel Methodology" (Islam et al. 2012b). This paper is under second review.

## 3.1 Background

The reliability assessment of a water supply system (WSS) is an important task in WSS planning and operations. It helps to compare and evaluate different plans, designs and maintenance options by identifying vulnerable areas in a WSS. Xu and Powell (1991) reported that reliability assessment helps to:

- identify weak areas in a system
- conduct a comparative analysis of alternative plans, designs and maintenance options and operational strategies
- assess the performance of a system against the desired level of service
- predict future operational performances, and
- estimate a balanced level of cost and service.

Reliability assessment of WSS has been extensively reported in the research and practice literature. However, there is no standard guideline or a methodology for performing a reliability assessment. Therefore, researchers, municipal engineers, urban planners, government agencies have provided great emphasis on the development of a standard methodology for evaluating reliability and system performance under emergency loading conditions (Lansey et al. 2002). The reliability assessment of a WSS is generally carried out under extreme conditions such as for fire-fighting demands, broken pipes, pump failures, power outages, control valve failures and insufficient storage capability (Lansey et al. 2002). In general, the reliability assessment of a WSS can be classified into two groups, namely, topological or mechanical reliability and hydraulic reliability (Ostfeld et al. 2002). However, in recent literature, some authors have investigated water quality reliability (Ostfeld et al. 2002; Xu and Powell 1991; Zhao et al. 2010). According to Ostfeld et al. (2002), topological reliability refers to the probability that a given network is connected and given component probabilities to remain operational at any time. Hydraulic reliability refers to the probability that a WSS provides an adequate volume of water with adequate pressure to consumers as per their demand under any condition over a period of time. Like hydraulic reliability, water quality reliability is assessed with respect to a predefined level/ range of selected water quality parameters (e.g., residual chlorine concentration). If the water quality parameter is within the prescribed range, the WSS is considered *reliable*, otherwise it is considered unreliable for water quality (Zhao et al. 2010).

Fujiwara and Ganesharajah (1993) established a reliability assessment methodology based on the Markov Chain. They express hydraulic reliability in terms of available pressure. In their method, they assumed that the effectiveness of the WSS from a node is reduced due to insufficient nodal pressure. Tabesh et al. (2001) presented an extended period (24 hours) reliability assessment method based on the semi-pressure driven simulation where nodal available water volume changes with the nodal available pressure. Similar to other investigators, they also reported the hydraulic and the mechanical reliability. Surendran et al. (2005) provide a peaking factor-based reliability assessment framework where demand is the only criterion for reliability. To address uncertainty and variability in consumer demand, they use demand peaking factors. Although the use of peaking factors can increase confidence in the reliability assessment, it also poses a risk of being an uneconomical, conservative assessment. Zhuang et al. (2011) present a methodology for reliability/availability assessment of a WSS based on an adaptive pump operation. In response to a pipe break, pump operations are adapted using various sizes of pump combinations. In their method, they evaluate hydraulic reliability in terms of available water to fulfill desired demand.

It is evident from a comprehensive literature review that different investigators assess reliability by comparing computed network dependent parameters (e.g., pressure or flow and residual chlorine) under emergency loading conditions with their desired minimum level of service. To compute hydraulic dependent parameters such as pressure and flow, continuity and energy equations expressed in terms of network independent parameters (e.g., roughness parameters, nodal demand) are solved using an analytical or simulation-based approach (Mays 2000). For water quality parameters (e.g., chlorine concentration), different algorithms solve the transport equations expressed in terms of different deterministic quality and hydraulic independent parameters. In all cases, a single value of each independent parameter, such as pipe roughness for a particular pipe or a single base demand for a particular node at a particular time, is used to estimate network-dependent parameters.

However, for a continuously changing WSS with many interactive subsystems, it is extremely difficult, even impossible, to estimate different independent parameters with 100% certainty. Hence, it is nearly impossible to estimate network dependent parameters with certainty using uncertain network independent parameters. A well-calibrated network model may provide a better estimation of independent parameters. However, in reality, the standard of hydraulic model calibration is often unsatisfactory(Islam et al 2011b). Therefore, a question arises, how reliable are the results of current reliability assessments? Are the WSS traditionally categorized as reliable systems really that reliable?

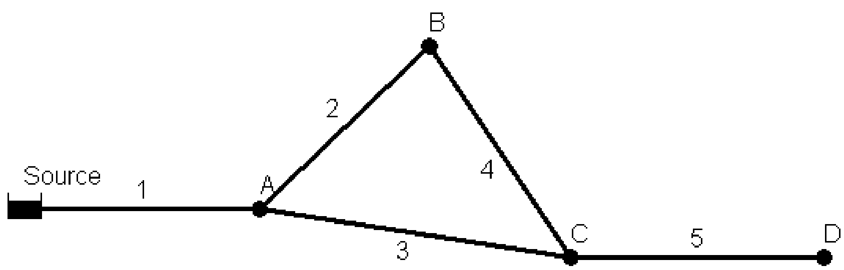


Figure 3.1: Layout of the example network

Table 3.1: Information of the example WSS

| Node Info. | | | Pipe Info. | | | |
|---|---|---|---|---|---|---|
| ID | Elevation, m | Demand, $m^3/h$ | ID | Length, m | Diameter, mm | C-factor |
| Source | 28 | 0 | 1 | 1000 | 200 | 100 |
| A | 0 | 8.1 | 2 | 800 | 150 | 100 |
| B | 0 | 7.4 | 3 | 1200 | 200 | 100 |
| C | 0 | 9.5 | 4 | 1000 | 150 | 100 |
| D | 0 | 12.5 | 5 | 2000 | 150 | 100 |

To highlight this issue, a simple WSS network taken from Shang and Uber (2008), as shown in Figure 3.1 has been adapted using modified model attributes. The network has five pipes and one water source. Table 3.1 provides the data for the example network. The network has been simulated for a steady state condition using demand-dependent simulation engine EPANET (Rossman 2000) which provides deterministic output of dependent parameters such as pressure at different nodes and flow through different pipes. In a second scenario, the example network has been re-simulated for a 10% decrease, arbitrarily, in C-factors in pipes 1 and 3, and a 10% increase in nodal demand at node D. Table 3.2 provides the pressure at different nodes and the flow through different pipes under normal condition (scenario 1) and changed network condition (scenario 2).

Table 3.2: Model results for normal and changed conditions

| Pressure, m | | | Flow, $m^3/h$ | | |
|---|---|---|---|---|---|
| Node ID | Scenario 1 | Scenario 2 | Link ID | Scenario 1 | Scenario 2 |
| Source | 0 | 0 | 1 | 37.5 | 38.75 |
| A | 26.86 | 26.53 | 2 | 10.41 | 11.41 |
| B | 26.51 | 26.12 | 3 | 18.99 | 19.24 |
| C | 26.47 | 26.04 | 4 | 3.01 | 4.01 |
| D | ***25.26*** | ***24.6*** | 5 | 12.5 | 13.75 |

From Table 3.2, it is evident that the dependent parameters have changed to a certain extent, due to the inherent uncertainties in the network independent parameters. If consumers' desired minimum level of service for pressure is 25m (Deb 1995; MacKenzie et al. 2002), then the deterministic solution of scenario 1 concludes that the network is fully satisfactory at all locations (nodes). However, if uncertainties exist in the network independent parameters, the network cannot fulfill the desired minimum level of service at all nodes. Although the example network is relatively small compared to a real WSS, just a small change in the independent parameters makes a difference in the calculated pressures and flows. In a real WSS consisting of hundreds of nodes, pipes and consumer demands, calculated results can be significantly different due to uncertainties inherent in the independent parameters. Therefore, reliability assessment results based on deterministic dependent parameters are subjected to uncertainties.

Alternative consideration of nodal pressure and consumer demand is another aspect of current practice for reliability assessment. Some investigators (e.g., Xu 1998) consider pressure as an only measure of hydraulic reliability whereas the other (e.g., Fujiwara and Ganesharajah 1993; Gupta and Bhave 1994) consider available water volume as a measure of hydraulic reliability. In reality, pressure and flow are two different aspects of consumers' requirements. For example, in a pressure-based reliability assessment, if a consumer receives a pressure less than the predefined minimum level of service then the reliability has been considered as *zero*. However, in reality, the consumer will continue getting water until the pressure reached to zero. In this situation, the consumer might not be satisfied due to lack of enough water pressure, but still the consumer is getting some service or *utility* from the system. Therefore, it is logical to consider both pressure and available demand in the estimation of hydraulic reliability.

Treatment of different types of reliabilities (e.g., mechanical, hydraulic or water quality reliability) is another issue in reliability assessment. In the literature, mechanical, hydraulic and water quality reliability assessments are carried out and interpreted separately. However, the main concern of consumers is overall reliability. To consumers, a reliable WSS will deliver safe water with desirable quality, quantity and continuity and maintain a desirable minimum level of pressure under any condition. To a household consumer, a 100% hydraulically reliable system is unreliable if water quality is not reliable; on the other hand, 100% reliable quality water will not satisfy a consumer if the consumer does not receive the requisite quantity of water with a desired minimum pressure. The main concern of a consumer is whether a WSS can fulfill his/her needs satisfactorily or not.

In this chapter, an innovative methodology has been developed to evaluate the overall reliability of a WSS and quantify the effects of uncertainties on network-independent parameters on assessment results. Overall reliability has been expressed in terms of the *utility* received by the consumer from a WSS in terms of water quantity, pressure and quality, and *belief* in the estimated utility which provides an estimate of how reliable are the traditional reliability assessment results. The term *belief* has been used to indicate the confidence in the estimated utility, which is different from traditional *belief* in the Dempster-Shafer belief sense.

For the proposed methodology, uncertain independent parameters are modeled using fuzzy sets. Fuzzy sets deal with vague and imprecise information (Zadeh 1965). Instead of crisp information, the fuzzy sets model the information with a degree of membership where the most likely value has a full degree of membership and the least likely values have the lowest or zero membership. Fuzzy sets have been widely applied to solve the real-life problems that are subjective, vague, and imprecise in nature (Smithson and Verkuilen 2006; Yang and Xu 2002). Since its conceptualization, fuzzy sets have been used in various engineering applications including civil and water engineering related applications. It has been used for modelling of complex systems, and handles uncertain and imprecise information effectively (Ross 2004). To harmonize the different types of reliabilities, instead of using water pressure, volume and quality, utilities generated from these services have been considered as a measure of reliability. Although the term "utility" has a broader meaning to economists, in this study, utility refers to the *quality of a WSS being serviceable to fulfill consumer needs for access to safe drinking water with desirable quality, quantity and continuity (pressure)*.

## 3.2 Proposed Methodology

In one hand, the proposed methodology estimates the reliability of a WSS based on the aggregated utilities, and on the other hand, quantifies the effects of uncertainties of WSS independent parameters on the estimated utility.

The reliability of a WSS has been expressed as $R\ (U, \mu)$, where $U$ is the utility gained from a WSS and $\mu$ is the *belief* in the calculated utility. The utility (U) of a WSS has been calculated based on the level of service received by a consumer from available water volume, pressure and quality. The utility obtained from the available pressure and volume has been considered as the hydraulic utility, whereas water quality utility has been estimated based on the levels of residual chlorine concentration. Based on the estimated hydraulic and quality utilities, an aggregated utility has been estimated as a measure of overall reliability of a WSS. The belief ($\mu$) of the aggregated utility has been estimated based on the uncertainties related to the network independent parameters. Using fuzzy dependent parameters, beliefs of the calculated hydraulic and water quality utilities have been evaluated and, finally, aggregated as a single belief of the calculated utility. Figure 3.2 shows the general framework of the proposed methodology.

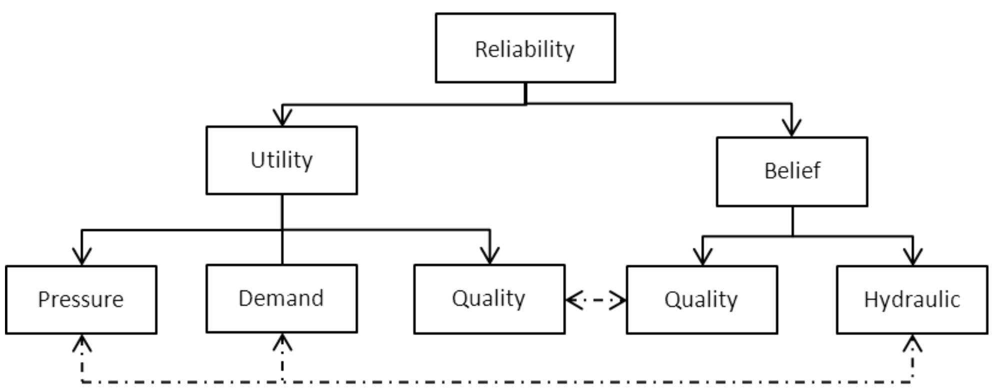


Figure 3.2: Reliability assessment methodology

As reported in previous studies (Gupta and Bhave 2007; Islam et al. 2011b; Revelli and Ridolfi 2002), it is assumed that the independent and dependent parameters are triangular fuzzy numbers (TFN). The most likely values of dependent parameters (e.g., pressure, quality, age, etc. of water for all nodes and flow, velocity, quality, etc. of water for all pipes) are estimated using the most likely values of the independent parameters (e.g., roughness coefficients, nodal demands, reservoir water levels, etc.). However, extreme values (i.e., the maximum and the minimum) of independent parameters do not necessarily produce the extreme values of dependent parameters, respectively (Gupta and Bhave 2007; Islam et al. 2011b). But, Gupta and Bhave (2007) show that some combinations of extreme values of independent parameters do indeed produce the extreme values of dependent parameters. The algorithm developed by Gupta and Bhave (2007) is used to estimate the extreme values of the dependent parameters for an extended period of simulation. Details of the estimation of extreme values of dependent parameters are later provided in Section 3.2.2. Figure 3.3 provides the conceptual basis for the belief estimation. In Figure 3.3 (a), all the independent and the calculated dependent parameters are assumed deterministic. Therefore, they have a full degree of membership of their values. However, in Figure 3.3 (b), all the independent and the dependent parameters are assumed fuzzy and they have varying degrees of membership.

If the estimated minimum values of dependent parameters are higher than the desired minimum level of service, then the belief of the calculated utility is one; if the estimated maximum values of dependent parameters are lower than the minimum level of service, then the belief of the calculated utility is zero. However, if the level of service is between the estimated minimum and maximum values of the dependent parameters, then the belief of the calculated utility is between 0 and 1(Figure 3.3 (c)). In Figure 3.3 (d), the estimated hydraulic and quality belief provides an aggregated belief of the calculated utility.

The proposed methodology requires (a) identification and fuzzification of different independent parameters, (b) three sets of WSS solutions for minimum, most likely and maximum values of dependent parameters (e.g., pressure in all nodes and flow in all pipes), and (c) the estimation of utility and belief. The solution of a calibrated model estimates the values of dependent parameters (for all nodes and pipes) under normal conditions, whereas the other two set solutions estimate the two sets of possible extreme values of dependent parameters (for all nodes and pipes). Details of the different steps have been discussed in the following sections. The EPANET (Rossman 2000) simulation engine and its source codes have been used for the WSS simulation. Different stages of the proposed methodology and EPANET toolkits functions have been implemented using MATLAB 7.10 (MathWorks 2010).

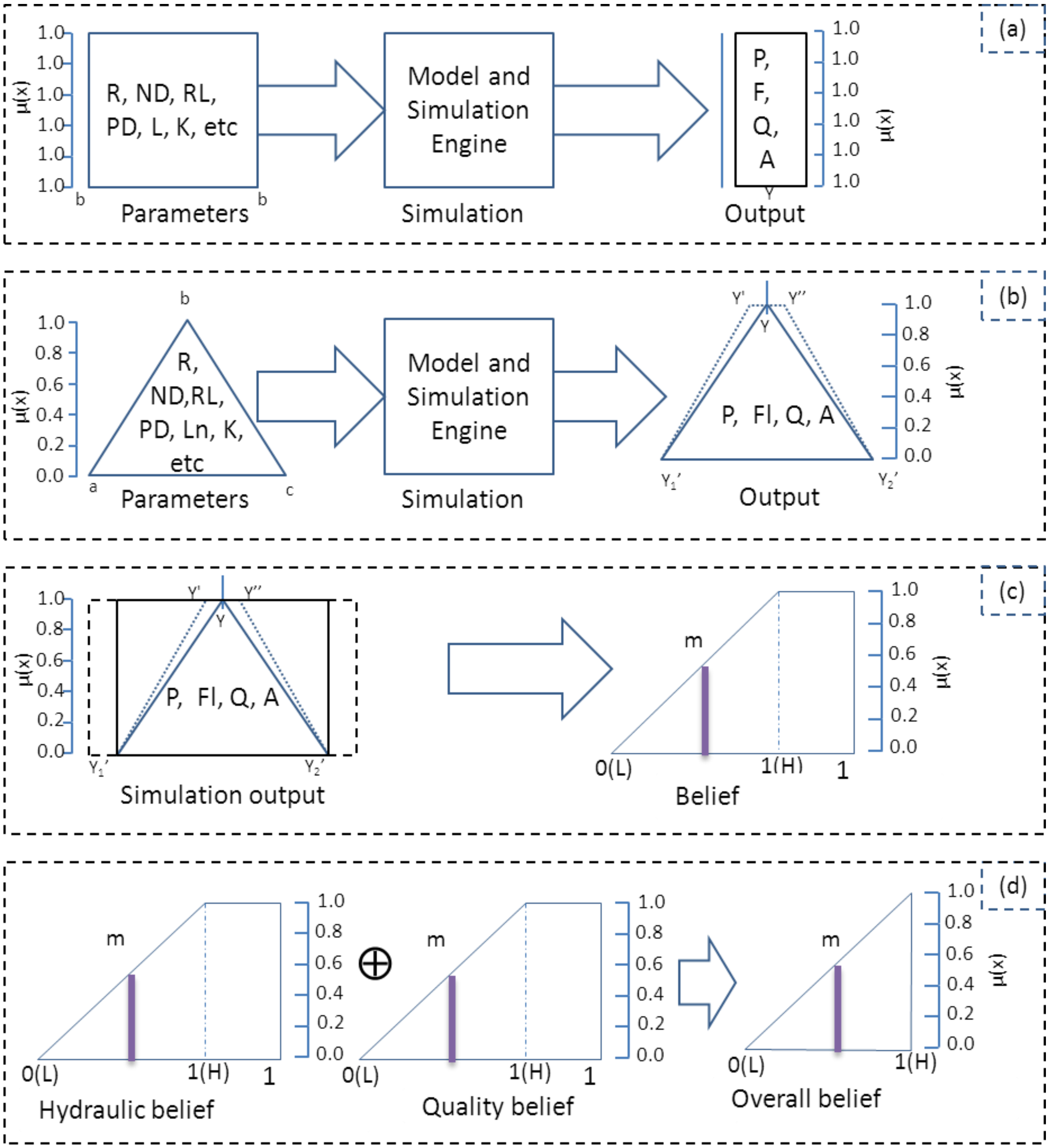


Figure 3.3: Conceptual framework of the belief estimation

R=Roughness coefficients; ND=Nodal demands; RL=Reservoir water levels; PD=Pipe diameters; $L_n$=Lengths of the pipes; K=Head loss coefficients; P= Pressure; FL= Flow; Q= Quality; A= Water age; a= Lower level values of independent parameters; b= The most likely values of independent parameters; c= Upper level values of independent parameters; $Y_1'$ = Lower level values of dependent parameters; $Y_2'$ = Upper level values of dependent parameters; Y= The most likely values of dependent parameters; In case of certain percentage of deviation of the most likely values of dependent parameters or in case of ZFN (instead of TFN) has been used for independent parameters, the most likely value Y could extend from two sides of the most likely values. In Figure 3.3 (b), Y' and Y'' represents the range of the acceptable deviation.

### 3.2.1 Identification and Fuzzification of Independent Parameters

Water supply systems are complex infrastructures. Modelling such infrastructures involves many parameters, such as pipe diameters, lengths, and roughness coefficients, nodal demands, water levels in reservoirs and pump characteristic curves, and performance characteristics of different valves and minor elements (Gupta and Bhave 2007). Among these parameters, some are relatively certain, such as pipe lengths; some are uncertain, such as roughness coefficients; and some are between, such as nodal demand, for which a statistical distribution can be generated if enough information is available (Revelli and Ridolfi 2002). Some of these uncertain parameters may have a significant impact on WSS, whereas some of them may have only a limited impact. The parameters that are relatively more uncertain and have significant impact on WSS simulation results are generally recommended for fuzzification. However, modelling of all WSS independent parameters as uncertain parameters will not reduce the trustworthiness of results; rather, it will increase the computational burden. Roughness coefficients, nodal demands and reservoir water levels are considered the most common imprecise parameters and may have a significant impact on the hydraulic results (Gupta and Bhave 2007; Revelli and Ridolfi 2002). Therefore, these three parameters can be selected as the most influential network independent parameters.

After the independent parameters are selected, the most likely (normal) and the extreme values of the selected parameters are defined. The values of independent parameters of a calibrated model can be used as the best estimate for the most likely values. The extreme values can be estimated based on reported literature values, industry experience and other supporting data or a percentage of the most likely value based on expert judgement. Fuzzification has been carried out using the minimum, most likely and maximum values of all the selected independent parameters. To fuzzify the data, generally triangular fuzzy numbers (TFN) or trapezoidal fuzzy numbers (ZFN) are used in literature (Lee 1996). All the selected parameters (e.g., roughness coefficients, nodal demands, reservoir water levels) have been fuzzified in order to belong to the corresponding set presented by Equation 3.1:

$$\mu_x: X \rightarrow [0,1] \qquad [3.1]$$

where $X$ is the possible range of a variable $x$ (network independent parameters) and $\mu_x$ is the membership function of $x$. Figure 3.4 shows the TFN and ZFN, and Equations 3.2 and 3.3 fuzzify the data in terms of TFN and ZFN, respectively.

$$\text{For TFN: } f(x;a,b,c) = \begin{cases} 0 & ,x < a \text{ or } c < x \\ \frac{(a-x)}{(a-b)} & ,a \le x \le b \\ \frac{(c-x)}{(c-b)} & ,b \le x \le c \end{cases} \qquad [3.2]$$

$$\text{For ZFN: } f(x;a,b,c,d) = \begin{cases} 0 & ,x<a \text{ or } d<x \\ \frac{(a-x)}{(a-b)} & ,a\le x\le b \\ 1 & ,b\le x\le c \\ \frac{(d-x)}{(d-c)} & ,c\le x\le d \end{cases} \qquad [3.3]$$

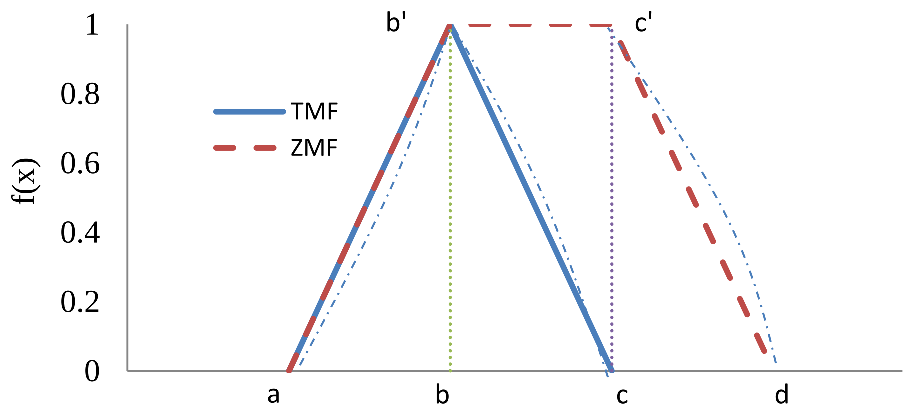


Figure 3.4: Triangular and trapezoidal fuzzy numbers

For a TFN, *a* is the minimum value, *b* is the most likely value and *c* is the maximum value of an independent parameter. For a ZFN, *a* is the minimum value, *d* is the maximum value and *b* and *c* are the two values which represent the interval of the most likely values. Although the fuzzy independent parameters are strictly triangular or trapezoidal with linear sides (e.g., *ab'* and *b'c* for TFN and *ab'* and *c'd* for ZFN), the corresponding fuzzy dependent parameters will be also triangular or trapezoidal but with curvilinear sides (e.g., *ab'* and *b'c* for TFN and *ab'* and *c'd* for ZFN; See Figure 3.4), because of the nonlinearity of the system (Revelli and Ridolfi 2002). However, the difference between the linear and the curvilinear sides is negligible (Gupta and Bhave 2007). Therefore, the fuzzy numbers for dependent parameters have been considered triangular or trapezoidal with linear sides. For this study, the triangular fuzzy number has been used. It is assumed that the fuzzified values of the independent parameters are in an *N*x3 matrix [*a b c*], where *N* is the number of an independent parameter. Nodal pressure has been used a hydraulic dependent parameter, whereas residual nodal chlorine concentration has been used as a quality dependent parameter.

### 3.2.2 Estimation of Extreme Values of Dependent Parameters

To estimate the extreme values of the dependent parameters, it is required to define all the fuzzy independent parameters. The following steps have been used to estimate the extreme values of dependent parameters:

1. Estimate the dependent parameters for the normal values of independent parameters [b] using EPANET. It is assumed that [Y] is the matrix of the simulated dependent parameters.

2. Change the first element of the matrix [*b*] with its maximum value from the matrix [*c*] (matrix of the maximum values of independent parameter), keeping all other elements of the matrix [*b*] the same.

3. Use EPANET to estimate the dependent parameters for the changed set of independent parameters. It is assumed that the results of dependent parameters are reported as $[D_n] = [D_1]$.

4. Reset all the independent parameters to their normal condition.

5. Repeat steps 2 to 4 for all the independent parameters.

6. Estimate the difference $[C] = [D_n] - [Y]$ for the simulated dependent parameters.

7. Maximize the first dependent parameter under the following conditions: If any element of the matrix [*C*] is greater than 0 ($C>0$), then the corresponding changed independent parameters should be maximum and if $C<0$ then the corresponding changed independent parameters should be a minimum value. The selected set of maximum and minimum independent parameter matrix (*Mx*) will produce the maximum value of first dependent parameter.

8. Run the simulation for the selected combination of extreme independent parameters and obtain the maximum value of first dependent parameter.

9. Repeat steps 7 and 8 for all the dependent parameters.

10. Minimize the first dependent parameter under the following conditions: If any element of the matrix [C] is greater than 0 (C>0), then the corresponding changed independent parameters should be minimum value and if C<0 then the corresponding changed independent parameters

should be maximum value. The selected set of minimum and maximum independent parameter matrix (*My*) will produce the first minimum dependent parameter.

11. Run the simulation for the selected extreme independent parameters and select the first minimum dependent parameters.

12. Repeat steps 10 and 11 for all the dependent parameters.

13. Repeat steps 1 to 12 for different time steps.

Based on the steps, the extreme values of the hydraulic dependent parameters for 24 hours can be estimated. However, the extreme values of the water quality dependent parameters require certain modifications in step 6 in the flowchart. There is a difficulty in the steady state water quality simulation using EPANET. Water quality simulation requires an extended period simulation (EPS). In the EPS water quality simulation, the quality time steps are much shorter than the hydraulic time steps to accommodate shorter travel times that can occur within a pipe (Rossman 2000). In EPANET, the default hydraulic time step is one hour, whereas the default quality time step is just five minutes. These default time steps have been adapted in this study. In step 6, a single value of the dependent parameter is compared to check the monotonicity for steady state hydraulic simulation. However, for water quality simulation, the corresponding values have been compared for an extended period simulation considering monotonicity in the EPS. During the comparison, it has been noted that changes in water quality parameters due to changes in the independent parameters are very small and monotonic with certain exceptions. For a particular node, approximately, 95% to 99% of the time, the water quality results show the monotonicity. About 1% to 5% of the time, nodal water quality parameters show no changes or reverse changes of very small magnitude which could result from the numerical instability of the EPANET computational engine. For simplicity, in this study, the impact of independent parameters on water quality dependent parameters has been considered monotonic. The extreme values of a water quality parameter (e.g., residual chlorine concentration) estimated in a similar way as extreme values of hydraulic depended parameters have been estimated with a modification in step 6.

Table 3.3: Maximum, most likely & minimum pressure values at different nodes

| Node ID | Pressure | | |
|---|---|---|---|
| | Maximum | Most Likely | Minimum |
| A | 27.53 | 26.86 | 26.15 |
| B | 27.23 | 26.51 | 25.75 |
| C | 27.20 | 26.47 | 25.70 |
| D | 26.19 | 25.26 | 24.24 |

For the WSS example (Figure 3.1), fuzzy dependent parameters have been estimated considering a ±0.5 m variation in the reservoir level (i.e., 27.5m, 28m, and 28.5m as the minimum, most likely and maximum value, respectively), ±5 variation in roughness coefficients (i.e., 95, 100, 105), and ±5% variation in nodal base demands from their normal values. In all simulations, first order bulk and wall reactions have been considered. Considering new plastic pipes, no wall demand for disinfectant has been considered (Rossman 2000). The modeled global bulk and wall coefficients have been -1 and 0, respectively. Following above mention steps, the possible maximum, the most likely and the minimum values of pressure at different nodes have been estimated (Table 3.3) under steady state condition. Using the above algorithm, EPS values for pressure and water quality parameters (e.g., chlorine) concentration have been estimated.

### 3.2.3 Reliability Estimation

The reliability of a WSS for a consumer is the utility related to consumers' satisfaction. A consumer will be satisfied when the desirable water is available to him with a desired quantity with desired pressure, and desired quality. Therefore, WSS reliability has been evaluated based on the consumers' satisfaction received for the services from a WSS, and expressed in terms of consumers' utilities. The utility has been used as a measure of reliability. If a consumer received guaranteed desired utility from a WSS with 100% satisfaction under any condition, then the WSS is considered fully reliable and vice versa. The consumer utilities from a WSS are depended on the available water volume, pressure and quality. Although the nodal pressure and the available water volume are strongly interrelated, both are independently important to a consumer. A consumer receiving water with low pressure and a consumer receiving the same volume of water with high pressure do not have a same level of satisfaction. Therefore, the hydraulic utility has been divided into demand utility and pressure utility.

### 3.2.3.1 Pressure Utility

In WSS reliability assessment literature, most of the investigators assume that if the available pressure in a node is higher than the desired minimum level of service, then the requirement for pressure is fully met; if available pressure is less than the desired minimum level of service, then the requirement for pressure is not met (Gupta and Bhave 1994). However, some authors consider a linear distribution of hydraulic reliability in terms of hydraulic availability in the range of minimum accepted pressure level and desired minimum pressure level. At the minimum acceptable pressure level, hydraulic reliability is assumed to be zero; at the desirable minimum pressure level, it is full and between the minimum acceptable and the desired minimum pressure level, reliability is expressed in terms of different functions (Fujiwara and Ganesharajah 1993). Similar to the traditional reliability, in this study, utility is considered to be zero when the pressure is equal or less than the accepted minimum level of pressure; full utility is achieved when the pressure is equal or higher than the desired minimum level of pressure and between these two pressures, utilities are interpolated linearly. Figure 3.5 shows the distribution of pressure utility at a particular node at a particular time. Equation 3.4 serves to model the pressure utility from a particular node at a particular time.

$$U_j(p) = \begin{Bmatrix} 0 & , \ P_j \le P_j^{mLoS} \\ \dfrac{(P_j - P_j^{mLoS})}{(P_j^{Des} - P_j^{mLoS})}, & P_j^{mLoS} > P_j > P_j^{Des} \\ 1 & , \ P_j \ge P_j^{Des} \end{Bmatrix} \qquad [3.4]$$

where, $U_j\,(p)$ is the pressure utility at a node $j$ at a particular time, $t$; $P_j$ is pressure a node $j$ at a particular time, $t$ under normal condition; $P_j^{mLos}$ is the acceptable minimum level of pressure, $P_j^{des}$ is the desired minimum level of pressure.

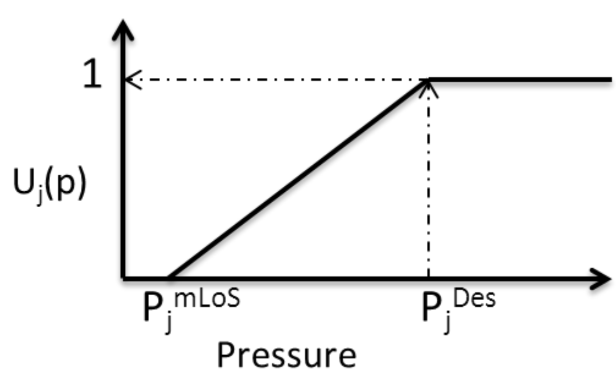


Figure 3.5: Distribution of pressure utility

#### 3.2.3.2 Demand Utility

In a demand-driven simulation (e.g., EPANET), nodal demands have been considered constant, irrespective of nodal pressure. However, in reality, the nodal available water volume depends on the available nodal pressure. Consumer satisfaction depends on both available pressure and available water. Therefore, the demand utility is evaluated based on the nodal available water. To estimate nodal available water volume under different pressures, Equation 3.5 has been used (Wagner et al. 1988).

$$D_j^{avl} = \begin{cases} D_j^{Des} \quad , & P_j \geq P_j^{Des} \\ D_j^{Des} \times \left[ \dfrac{(P_j)}{(P_{Des})} \right]^{\frac{1}{n}}, & 0 < P_j < P_j^{Des} \\ 0 & P_j = 0 \end{cases} \qquad [3.5]$$

where, $D_j^{Des}$ is the desired minimum nodal demand at node *j* at a particular time; $D_j^{avl}$ is the available water at node *j* at particular time, *t*; *n* is the pressure exponent which normally varies in between 1.5 to 2.0 (Cheung et al. 2005), and the other parameters are defined as before.

Based on available water and nodal pressure, Equation 3.6 has been used to estimate the demand utility at a particular node at a particular time.

$$U_j(d) = \begin{cases} 1 \quad , & P_j \geq P_j^{des} \\ \dfrac{D_j^{av}}{D_j^{des}}, & 0 > P_j > P_{des} \\ 0 & P_j = 0 \end{cases} \qquad [3.6]$$

where, $U_j(d)$ is the demand utility at node *j* at a particular time , *t*, and other parameters are defined as before.

#### 3.2.3.3 Degree of Belief for Hydraulic Utility

As both available pressure and available demand are directly pressure dependent, a single belief function, termed "hydraulic belief" has been used. Equation 3.7 serves to estimate the belief of the estimated hydraulic utility (pressure and demand utility).

$$\mu_j(hu) = \begin{Bmatrix} 0 & , & P_j^{mLoS} > P_j^H \\ \dfrac{(P_j^H - P_j)}{(P_j^H - P_j^L)}, & & P_j^L > P_j > P_j^H \\ 1 & , & P_j^{Des} < P_j^L \end{Bmatrix} \qquad [3.7]$$

where, $\mu_j(hu)$ is the belief in the calculated hydraulic utility at node *j* at a particular time, *t*; $P_j^L$ and $P_j^H$ are the estimated lowest pressure and highest pressure at the particular node, *j* and at a particular time, *t*, respectively, and other parameters are defined as before.

#### 3.2.3.4 Water Quality Utility

If a consumer receives desired quality water from a node under any condition, then the node is considered as having full water quality utility. If the quality of water drops from the desired level to the minimum acceptable level, then the water quality utility also drops from full utility to zero water quality utility. If water quality lies between the desired and acceptable minimum quality level, then the water quality utility is interpolated between 0 and 1. Although, water quality is a function of various physical, chemical and microbiological parameters, for this study only residual chlorine concentration in the available water has been used as a measure of water quality utility. If fact, residual chlorine is one of the best cost effective indicators of the variability of water quality in a WSS (Fisher et al. 2011).

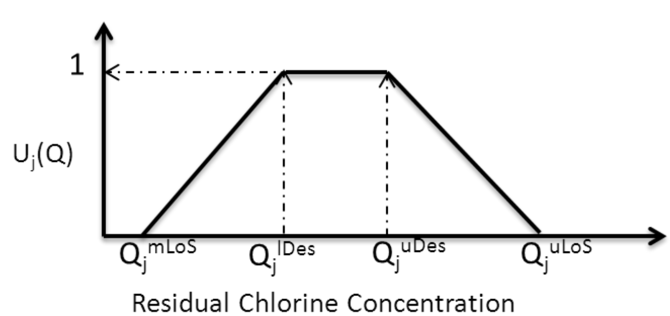


Figure 3.6: Distribution of water quality utility

Four levels of chlorine concentrations, namely, the acceptable minimum level of concentration ($Q_j^{mLoS}$), the lower level of the desired concentration ($Q_j^{lDes}$), the upper level of the desired concentration ($Q_j^{uDes}$) and the unacceptable level of concentration ($Q_j^{uLoS}$), have been used to define water utility from a residual chlorine concentration (Figure 3.6). As a low level of chlorine concentration makes the favorable environment in WSS for different microorganism regrowth and biofilm formation (Lund and Ormerod 1995), water quality utility has been considered as zero after a minimum threshold chlorine concentration. Similarly, since an excessive chlorine concentration is not desirable in drinking water, an upper level of desired chlorine concentration ($Q_j^{uDes}$) and an unacceptable level of chlorine concentration ($Q_j^{uLoS}$), have been considered. If the residual chlorine concentration in water is higher than the upper level of the desired concentration ($Q_j^{uDes}$), the excess chlorine favors reaction with natural organic matter (NOM) which produces potentially harmful chlorinated by-products and offensive taste and odor to consumers (Fisher et al. 2011). Therefore, the water quality utility starts to reduce and will totally diminish to zero if the chlorine concentration reaches the unacceptable level of concentration ($Q_j^{uLoS}$). Equation 3.8 has been used to model water quality utility for a particular node at a particular time.

$$U_j(q) = \left\{ \begin{array}{ll} 0 & , \; Q_j \le Q_j^{mLoS} \text{ or } Q_j \ge Q_j^{uLoS} \\ \dfrac{(Q_j - Q_j^{mLoS})}{(Q_{des} - Q_j^{LoS})}, & Q_j^{mLoS} > Q_j > Q_j^{lDes} \\ \dfrac{(Q_j^{uLoS} - Q_j)}{(Q_j^{uLoS} - Q_j^{uDes})}, & Q_j^{uLoS} > Q_j > Q_j^{uDes} \\ 1 & , \; Q_j^{lDes} \le Q_j \le Q_j^{uDes} \end{array} \right\} \qquad [3.8]$$

where, $U_j(q)$ is the water quality utility at node $j$ at time, $t$ ; $Q_j$ is the water quality at normal condition at node $j$ at time, $t$; $Q_j^{mLoS}$ is the acceptable minimum level of service, $Q_j^{lDes}$ is the lower level of desired level of service ; $Q_j^{uDes}$ is the upper limit of desired (full utility if the chlorine concentration lies in between $Q_j^{lDes}$ and $Q_j^{uDes}$); and $Q_j^{uLoS}$ is the maximum level concentration that generates water quality utility. A concentration higher than this level has no water quality utility.

#### 3.2.3.5 Degree of Belief for Water Quality Utility

Similar to the estimated hydraulic utility, estimated water quality utility subjected to uncertainties and a degree of belief has been incorporated in the evaluated water quality utility. Like the hydraulic utility belief, Equation 3.9 has been used to estimate the degree of belief of the calculated water quality utility at a particular node at a particular time.

$$\mu_j(qu) = \begin{cases} 0 & , \ Q_j^{mLoS} > Q_j^H \\ \dfrac{(Q_j^H - Q_j)}{(Q_j^H - Q_j^L)}, & Q_j^L > Q_j > Q_j^H \\ 1 & , \ Q_j^{mLoS} < Q_j^L \end{cases} \qquad [3.9]$$

where, $\mu_j\,(qu)$ is the degree of belief of the water quality utility at node *j* at time, t; $Q_j^L$ is the estimated lowest water quality at a particular node *j* at time, t; $Q_j^H$ is the estimated highest water quality at node *j* at time, t, and the other parameters are defined as before.

#### 3.2.3.6 Cumulative Utility

Based on the estimated demand utility, pressure utility and water quality, an aggregated utility at a node at a particular time is estimated. Various aggregation operators (Sadiq and Manuel J. Rodriguez 2005) could have been used to aggregate the estimated different kinds of utilities. However, to meet all the requirements, t-norm (‘AND’-type) operators must be used. Then again, if a single parameter suffices to meet the criterion, a t-conorm (‘OR’-type) operator can be used. To meet all the utility requirements, pressure utility, demand utility and water quality utility criteria must be fulfilled at all times, therefore, a t-norm operator has been used. However, the pressure utility and the demand utility are strongly interrelated. Equation 3.10 has been used to estimate the hydraulic utility at a particular node, *j* at particular time, *t* combining the pressure and demand utilities.

pressure and demand utilities.

$$U_j(hu) = \sqrt{U_j(p) \times U_j(d)} \qquad [3.10]$$

where, $U_j\ (hu)$ is the hydraulic utility at junction *j* at time, *t*; $U_j\,(p)$ is the pressure utility at node *j* at a particular time, *t*; $U_j\,(d)$ is the demand utility at node *j* at a particular time, *t*.

To combine hydraulic utility and quality utility, maximum of t-norm, “AND” operators has been used (Equation 3.11).

$$U_j(c) = \min\left[U_j(hu), U_j(qu)\right] \quad [3.11]$$

where $U_j(c)$ is the combined utility at junction $j$ at time, $t$; and other parameters are defined as before.

Equation 3.12 has been used to estimate the aggregated belief of the combined utility.

$$\mu_j(c) = \sqrt{\mu_j(hu) \times \mu_j(qu)} \quad [3.12]$$

where, $\mu_j(c)$ is combined belief at junction $j$ at time, $t$; and other parameters are defined as before.

#### 3.2.3.7 General Solutions

Figure 3.7 shows the general solution domain for the reliability solutions based on the proposed methodology. Note that a utility without a belief and a belief without a utility are not practical, therefore, no solution exits along the both axes (BC and CD), except a solution at origin (0, 0). Except for these two boundary lines, conceptually, a solution can exist anywhere in the solution domain. A solution at the bottom half of
Figure 3.7 (region Y) where belief is always below 0.5 has actual reliability less than the reliability estimated by traditional reliability assessment.

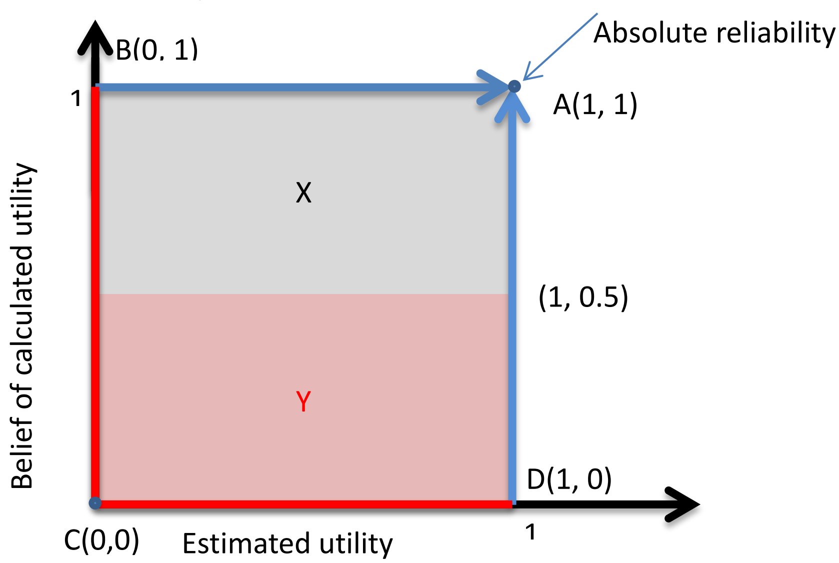


Figure 3.7: General solution domain

This is because if there is no uncertainty with different independent parameters, estimated belief will be always 0.5, which is the basic assumption in the traditional approach. However, a solution in the upper half of Figure 3.7 (region X) has a degree of belief higher than the traditional reliability estimates. For a new WSS, designed reliability should stay in the region X. A solution at the top right corner A (1, 1) conceptually represents the absolute reliability of the system. A solution other than this point is subjected to uncertainties. Therefore, for a system where high reliability is necessary, such as a WSS to supply water to a hospital or to a nuclear power plant, the solution should stay closer to the top right corner of Figure 3.7 (i.e., at point A (1, 1)). In addition, the higher the uncertainties in the estimate, the lower the belief of the calculated utilities without changing the estimated utilities. To demonstrate this phenomenon, the example network has been solved with an average reservoir level of 26 m and ±0.5 and ±1.0 m reservoir level variations.

Figure 3.8 shows the hydraulic reliabilities at different times in a day under two different levels of uncertainties (reservoir level variations ±0.5 and ±1.0 m). From Figure 3.8, it is evident that with increased uncertainties in the independent parameters, the solution moves down from the absolute reliability position, indicating the lower beliefs to the calculated utilities.

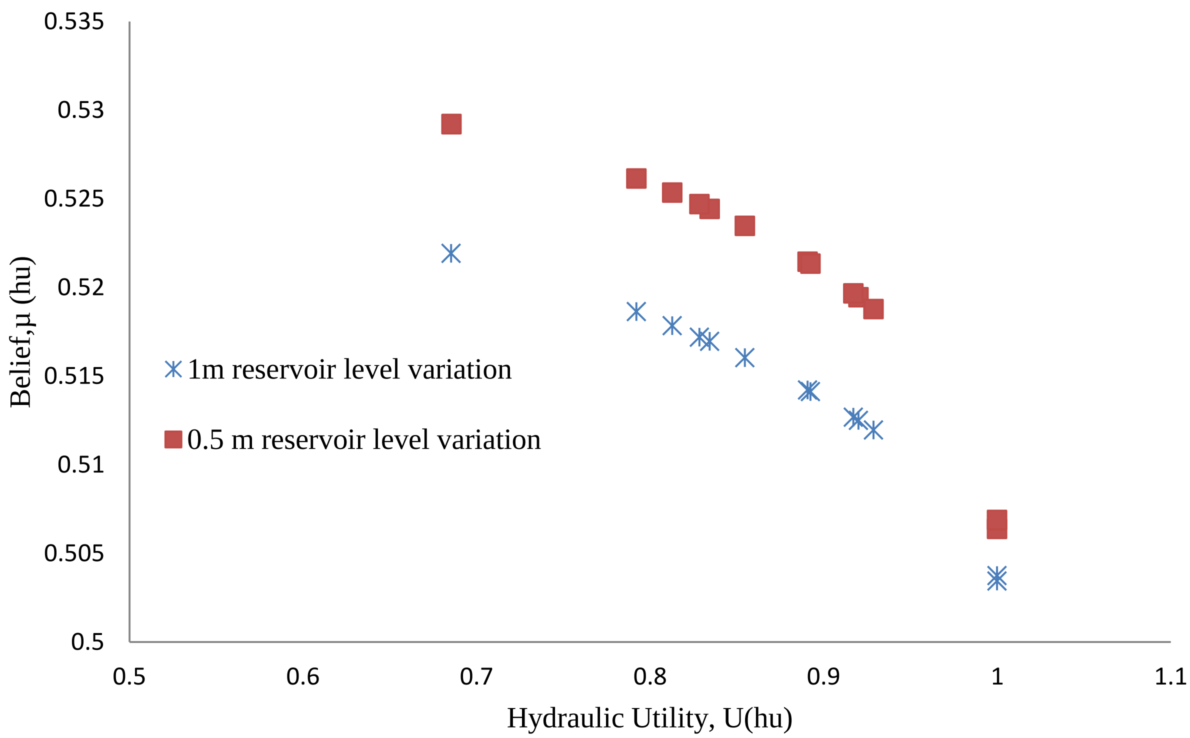


Figure 3.8: Hydraulic reliability at Node D under different level of uncertainties

Table 3.4: EPS reliability results for Node D of the example network

| Time, hr. | Pressure, m | | | Demand, m3/h | | Utility | | | Residual Chlorine, mg/l | | | Quality | | Combined | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Max. | Normal | Min. | Base | Available | Pressure | Demand | Belief | Max. | Normal | Min. | Utility | Belief | Utility | Belief |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| 0-2 | 26.09 | 25.51 | 24.92 | 4.94 | 4.94 | 1.00 | 1.00 | 0.51 | 0.67 | 0.67 | 0.67 | 1.00 | 1.00 | 1.00 | 0.71 |
| 2-4 | 26.05 | 25.46 | 24.86 | 5.19 | 5.19 | 1.00 | 1.00 | 0.51 | 0.62 | 0.62 | 0.62 | 1.00 | 1.00 | 1.00 | 0.71 |
| 4-6 | 24.56 | 23.70 | 22.76 | 11.38 | 11.07 | 0.87 | 0.97 | 0.52 | 0.57 | 0.57 | 0.57 | 1.00 | 1.00 | 0.92 | 0.72 |
| 6-8 | 21.64 | 20.22 | 18.63 | 18.69 | 16.81 | 0.52 | 0.90 | 0.53 | 0.53 | 0.53 | 0.52 | 1.00 | 1.00 | 0.69 | 0.73 |
| 8-10 | 22.91 | 21.73 | 20.42 | 15.88 | 14.80 | 0.67 | 0.93 | 0.53 | 0.57 | 0.56 | 0.55 | 1.00 | 1.00 | 0.79 | 0.73 |
| 10-12 | 23.16 | 22.04 | 20.79 | 15.25 | 14.32 | 0.70 | 0.94 | 0.53 | 0.57 | 0.57 | 0.56 | 1.00 | 1.00 | 0.81 | 0.72 |
| 12-14 | 24.17 | 23.23 | 22.21 | 12.56 | 12.11 | 0.82 | 0.96 | 0.52 | 0.57 | 0.56 | 0.55 | 1.00 | 1.00 | 0.89 | 0.72 |
| 14-16 | 24.68 | 23.84 | 22.93 | 11.00 | 10.74 | 0.88 | 0.98 | 0.52 | 0.56 | 0.55 | 0.54 | 1.00 | 1.00 | 0.93 | 0.72 |
| 16-18 | 23.44 | 22.36 | 21.17 | 14.56 | 13.77 | 0.74 | 0.95 | 0.52 | 0.55 | 0.54 | 0.53 | 1.00 | 1.00 | 0.83 | 0.72 |
| 18-20 | 23.36 | 22.27 | 21.07 | 14.75 | 13.92 | 0.73 | 0.94 | 0.52 | 0.55 | 0.55 | 0.54 | 1.00 | 1.00 | 0.83 | 0.72 |
| 20-22 | 25.01 | 24.22 | 23.39 | 9.88 | 9.72 | 0.92 | 0.98 | 0.52 | 0.56 | 0.56 | 0.55 | 1.00 | 1.00 | 0.95 | 0.72 |
| 22-24 | 25.84 | 25.22 | 24.58 | 6.31 | 6.31 | 1.00 | 1.00 | 0.51 | 0.56 | 0.55 | 0.54 | 1.00 | 1.00 | 1.00 | 0.71 |

Note: Assigned initial nodal residual chlorine concentrations high enough to ensure desired residual chlorine concentration for the first few hours at different nodes (shaded)

Using the developed methodology, different utilities for the example network under normal operating condition have been estimated. Table 3.4 shows the EPS reliability (24 hours) results for node D of the example network (Figure 3.1). From columns (15) and (16), it is evident that there is no time interval where the WSS is absolutely[2] reliable. If pressure, demand and water quality utilities have been considered separately, as per traditional reliability assessment method, the WSS system will be fully reliable at some points of the day. However, due to the uncertainty in the different independent parameters, the beliefs on calculated utilities are matters for concern. Note that if the initial residual chlorine concentrations at different nodes start at zero, it takes up to 8 hours to reach a residual chlorine concentration at the critical node. During these hours, the water quality utility at the critical node is very small or zero.

To avoid these zero utilities, an initial residual chlorine concentration is assigned at each node to ensure the desired concentration at each node for the first few hours (shaded part of Table 3.4). In a real WSS, this does not happen because the WSS supplies water after enough water is flushed; if the network is simulated for an existing operating condition, initial residual chlorine concentration will show up from the beginning of the simulation.

#### 3.2.3.8 System Utility

Estimated pressure, demand and water quality utilities provide a snapshot utility of different nodes at a particular time. However, these estimated utilities cannot provide utility as a whole in a WSS. Therefore, the overall system utility has been estimated to evaluate the performance of the system as a whole. The overall system utility is defined as a utility received from a WSS as a whole over a certain period of time. Equation 3.13 has been used to estimate the overall aggregated system utility for a particular time. In this equation, desired demand is used as weighted factors for the aggregated system utility.

$$U_t(su) = \frac{\sum_{j=1}^{N} D_j^{Des} \times U_j(c)}{\sum_{j=1}^{N} D_j^{Des}} \qquad [3.13]$$

[2] It is impossible design an absolute reliable system without considering total uncertainties in the system which is also impossible. In this chapter, the term “absolute reliability” has been used conceptually to define a target for a more reliable system.

where, all the parameters have their usual meaning as defined previously.

For an aggregated utility over a period of time, Equation 3.14 has been used. In this equation, desired system demand over the period has been used as a weighted factor in the aggregation.

$$U(su) = \frac{\sum_{t=0}^{T} D_t^T \times U_j(su)}{\sum_{t=0}^{T} D_t^T}$$ [3.14

where, $D_t^T$= total desired system demand over the period of time, and all the other parameters have their usual meaning as defined previously.

The belief of the aggregated utility has been defined in a similar way. Equation 3.15 has been used to estimate the overall belief of the calculated system utility for a particular time and Equation 3.16 has been used to estimate the overall belief of the calculated system utility over a period of time.

$$\mu_j(s) = \frac{\sum_{j=1}^{N} D_j^{av} \times \mu_j(C)}{\sum_{j=1}^{N} D_j^{av}}$$ [3.15]

where, all the parameters have their usual meaning as defined previously.

$$\mu(s) = \frac{\sum_{t=0}^{T} D_t^{Tot} \times \mu_t(C)}{\sum_{t=1}^{T} D_t^{Tot}}$$ [3.16]

where, $D_t^{Tot}$= total available water for the whole WSS over the period and all the other parameters have their usual meaning as defined previously.

Table 3.5 shows the system utility and the system belief of the example WSS in normal operating condition. From Table 3.5, it is evident that the absolute reliability has been not achieved at any time, even in normal operating conditions. Even though the estimated system utility at time 0-4am has been one, due to the degree of belief which is less than one, it is not possible to consider it as an absolute reliability. From Table 3.5, shows the system utility and the system belief of the example WSS in normal conditions.

Table 3.5: System utility for Example WSS

| Time, hr. | System Utility | System Belief |
|---|---|---|
| 0-2 | 1.000 | 0.904 |
| 2-4 | 1.000 | 0.904 |
| 4-6 | 0.966 | 0.717 |
| 6-8 | 0.815 | 0.724 |
| 8-10 | 0.883 | 0.721 |
| 10-12 | 0.896 | 0.721 |
| 12-14 | 0.947 | 0.718 |
| 14-16 | 0.971 | 0.717 |
| 16-18 | 0.910 | 0.720 |
| 18-20 | 0.907 | 0.720 |
| 20-22 | 0.924 | 0.720 |
| 22-24 | 0.964 | 0.717 |
| Overall | 0.917 | 0.732 |

### 3.3 Model Implementation and Demonstration

The proposed methodology has been implemented and demonstrated through a case study. The example WSS represents a simplified version of a part of a WSS (Islam et al. 2011b). Figure 3.9 shows the layout of the example WSS with necessary data. The example WSS has 27 nodes connected by 40 pipes with a total length of 19.5 km. Water is supplied by gravity from two elevated reservoirs (reservoir 1 and reservoir 2) with the total head of 90 m, and 85 m, respectively. Pipe lengths vary from 100 m to 680 m, and pipe diameters vary from 200 mm to 700 mm. The base demand at different nodes varies from 33.33 l/s to 133.33 l/s, and the demand multipliers ranges from 0.38 at 5am to 1.53 at 9 am. The chlorine concentration at both reservoirs is assumed at 0.80 mg/l. Assumed reaction parameters are the same as the parameters used in the previous example network (Figure 3.1). Detail information on pipe length, diameter, roughness coefficient, nodal connectivity, and nodal hourly base demand and demand multipliers[3] and two reservoirs head have been provided in Table 3.6.

[3] In hydraulic network modelling, base demand is the demand that the modelers assign to any particular node. For steady state simulation, it does not change. However, water demand changes

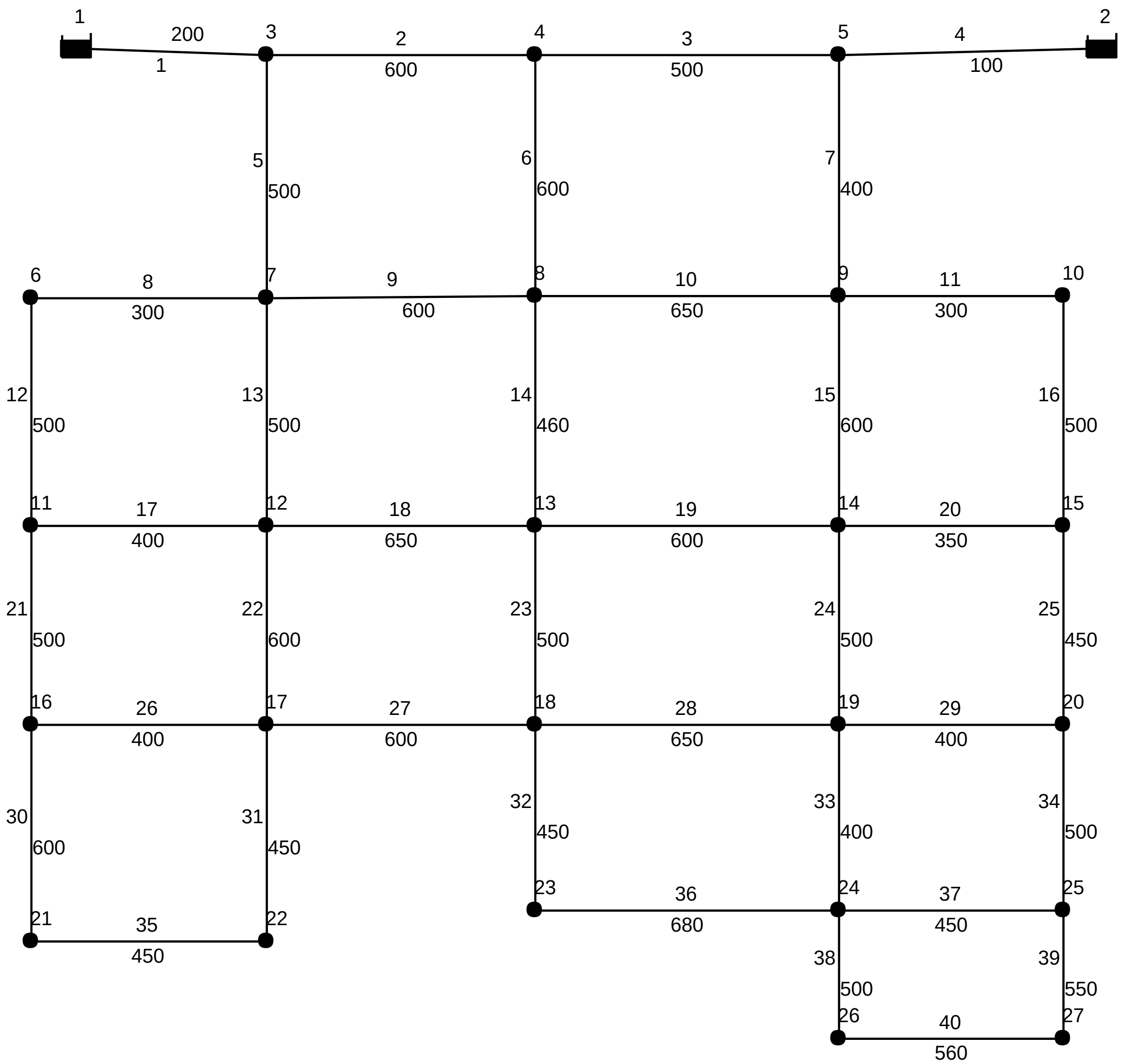


Figure 3.9: Layout of the study example WDS (pipe length not to the scale)

The WSS is considered to be an undamaged system and all parameter values have been considered as calibrated values in normal conditions. Parameters such as roughness coefficients, nodal demands, reservoir water levels, pipe diameters, length of the pipes, head loss coefficients, and quality parameters are uncertain parameters. For this case study, only the roughness coefficients, nodal demands, reservoir water levels and chlorine concentration at sources have been taken as uncertain independent parameters.

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continuously over time. To incorporate this change in demand, demand multipliers have been used. This is the ratio of demand at any time to base demand.

Table 3.6 : Information of the example WDS

| Node Information | | Pipe information | | | | | | DM | |
|---|---|---|---|---|---|---|---|---|---|
| Node Id | BD (l/s) | Pipe Id | U/S Node | D/S Node | L (m) | D (mm) | R | Hr | MF |
| 3 | 83.3 | 1 | 1 | 3 | 200 | 700 | 100 | 1 | 0.41 |
| 4 | 100.0 | 2 | 3 | 4 | 600 | 600 | 100 | 2 | 0.38 |
| 5 | 66.7 | 3 | 4 | 5 | 500 | 600 | 95 | 3 | 0.38 |
| 6 | 66.7 | 4 | 2 | 5 | 100 | 675 | 100 | 4 | 0.45 |
| 7 | 50.0 | 5 | 3 | 7 | 500 | 675 | 100 | 5 | 0.83 |
| 8 | 133.3 | 6 | 4 | 8 | 600 | 600 | 95 | 6 | 1.53 |
| 9 | 83.3 | 7 | 5 | 9 | 400 | 650 | 100 | 7 | 1.46 |
| 10 | 83.3 | 8 | 7 | 6 | 300 | 300 | 90 | 8 | 1.30 |
| 11 | 100.0 | 9 | 7 | 8 | 600 | 450 | 95 | 9 | 1.24 |
| 12 | 66.7 | 10 | 9 | 8 | 650 | 450 | 95 | 10 | 1.28 |
| 13 | 100.0 | 11 | 9 | 10 | 300 | 300 | 100 | 11 | 1.14 |
| 14 | 50.0 | 12 | 6 | 11 | 500 | 250 | 85 | 12 | 0.87 |
| 15 | 83.3 | 13 | 7 | 12 | 500 | 500 | 95 | 13 | 0.89 |
| 16 | 50.0 | 14 | 8 | 13 | 460 | 500 | 95 | 14 | 0.87 |
| 17 | 100.0 | 15 | 9 | 14 | 600 | 500 | 95 | 15 | 1.06 |
| 18 | 50.0 | 16 | 10 | 15 | 500 | 250 | 110 | 16 | 1.21 |
| 19 | 50.0 | 17 | 12 | 11 | 400 | 300 | 100 | 17 | 1.15 |
| 20 | 100.0 | 18 | 12 | 13 | 650 | 400 | 90 | 18 | 1.18 |
| 21 | 50.0 | 19 | 13 | 14 | 600 | 400 | 85 | 19 | 1.04 |
| 22 | 83.3 | 20 | 14 | 15 | 350 | 300 | 90 | 20 | 1.06 |
| 23 | 83.3 | 21 | 11 | 16 | 500 | 250 | 90 | 21 | 0.87 |
| 24 | 50.0 | 22 | 12 | 17 | 600 | 400 | 110 | 22 | 0.70 |
| 25 | 83.3 | 23 | 13 | 18 | 500 | 450 | 90 | 23 | 0.60 |
| 26 | 66.7 | 24 | 14 | 19 | 500 | 400 | 95 | 24 | 0.40 |
| 27 | 50.0 | 25 | 15 | 20 | 450 | 250 | 100 | | |
| | | 26 | 17 | 16 | 400 | 300 | 105 | | |
| | | 27 | 18 | 17 | 600 | 350 | 100 | | |
| | | 28 | 18 | 19 | 650 | 400 | 95 | | |
| Node Information | | 29 | 19 | 20 | 400 | 300 | 100 | | |
| Res. ID | Head (m) | 30 | 16 | 21 | 600 | 200 | 100 | | |
| 1 | 90 | 31 | 17 | 22 | 450 | 300 | 90 | | |
| 2 | 85 | 32 | 18 | 23 | 450 | 300 | 95 | | |
| | | 33 | 19 | 24 | 400 | 300 | 85 | | |

BD=Base demand; L=Length; D=Diameter; R=Roughness; DM= Demand multiplier; MF = Multiplying factor

Table 3.6: Information of the example WDS (Continued)

| Node Information | | | Pipe information | | | | | | DM | |
|---|---|---|---|---|---|---|---|---|---|---|
| Node Id | BD (l/s) | | Pipe Id | U/S Node | D/S Node | L (m) | D (mm) | R | Hr | MF |
| | | | 34 | 20 | 25 | 500 | 250 | 105 | | |
| | | | 35 | 22 | 21 | 450 | 250 | 90 | | |
| | | | 36 | 23 | 24 | 680 | 250 | 110 | | |
| | | | 37 | 24 | 25 | 450 | 300 | 95 | | |
| | | | 38 | 24 | 26 | 500 | 300 | 90 | | |
| | | | 39 | 25 | 27 | 550 | 250 | 95 | | |
| | | | 40 | 26 | 27 | 560 | 250 | 95 | | |

BD = Base demand; L = Length; D = Diameter; R=Roughness; DM = Demand multiplier; MF = Multiplying factor

According to the procedure described earlier, the minimum, the most likely and the maximum values of the independent parameters are selected. The deviation for the reservoir levels ±0.5 m, for the roughness coefficients ±5, for the nodal base demands ± 5% deviations (Gupta and Bhave (2007)) and for chlorine concentration at both sources ±0.5 mg/l, from their normal values have been considered to estimate the two extreme values of those independent parameters. Assumed minimum and desired minimum levels of services (pressure) have been 15m and 25m, respectively. Similarly, the acceptable and desired minimum levels of residual chlorine concentrations have been 0.2 mg/l and 0.5mg/l, respectively. Following the procedure described earlier in Section 3.2.2, the minimum, most likely and maximum values of nodal pressure and nodal residual chlorine concentration over a period of 24 hours have been estimated. Different reliability estimation parameters have been evaluated based on the estimated normal, minimum and maximum values of nodal pressure and nodal residual chlorine concentration.

## 3.4 Results and Discussion

Two scenarios have been investigated. In the first scenario, reliabilities have been assessed under normal operating conditions, whereas in the second scenario reliabilities have been assessed under failure conditions. Note that in this case, a zero initial quality has been established at each node. From the calculated results, it reveals that under the normal condition, the WSS has the capabilities to provide enough water with desirable quality and desirable pressure during the simulation period. It is also observed that in all cases, the desired levels of water volume, pressure and quality are always higher than the minimum values of pressure and quality (except for the first three hours of operation). Therefore, it can be concluded that the WSS has absolute reliability in normal conditions during the simulation period.

According to the definition of reliability, reliability assessment in normal conditions is not sufficient to understand the performance of a WSS under emergency conditions. Therefore, reliability assessments are necessary under all possible extreme conditions. This also includes failure of multiple pipes simultaneously, as well as the failure of the reservoir connection line during a fire-fighting event and / or power or pumping station failures. Although an unlimited number of failure scenarios are possible, the probability of multiple pipe failures at the same time is very low (Tabesh et al. 2001). It can be assumed that pipe failures are independent (Su et al. 1987).In addition, if any dependency exists, it will be negative dependency. For example, if a pipe failure occurs in the system, it will reduce the pressure in the system and due to reduced system pressure, the probability of another pipe failure will decrease. However, in the case of large WSS, the influence of pressure might not be significant. Other pipe failure factors, such as vandalism or traffic loadings may cause pipe failures which are totally independent events.

As the purpose of this article is to demonstrate a novel methodology for reliability assessment, all the possible failure scenarios have not been investigated. For this study, one pipe failure at a time has been assumed. In addition, no fire-fighting demand has been considered. There are various techniques and methods available to estimate the probability of pipe failure, time for repairs, and mean time between the failures (MTBF). Interested readers should refer to Chapter 18 of Mays (2000). In this study, one random pipe failure at a time has been generated using a uniform distribution in the range of [1, N] where N is the pipe number. The reliability assessment has been carried out only for one day. Therefore, the impacts of repair time and repair interval have not been investigated. However, these parameters are very important aspects of WSS reliability assessment.

From the analysis of pressure, flow and residual chlorine concentration over the simulation period, it is found that the most critical node in the network has been node 27. This node received minimum pressure at all times. As stated earlier, during normal operating conditions, the hydraulic utility and the degree of belief at all time steps are always units that indicate absolute reliability under normal conditions. The uncertainties in the network independent parameters cannot influence the hydraulic utility of the system. However, after initial chlorine concentration reaches to the most critical point (i.e., after 3 hours network operation), the water quality utility for the WSS is also one.

Analyzing different pipe failure scenarios, it has been found that the most critical node (i.e., node 27) received the minimum pressure and minimum residual chlorine concentration when pipe 4 has been disconnected from the network. This is justifiable, since node 27 is the furthest node from both sources, and this node is only connected by two pipes. Figure 3.10 shows that the available pressure at the identified critical node (node 27) under different pipe break situations. Due to the lack of considerable chlorine demand in the network, no considerable effect has been observed in the residual chlorine concentrations.

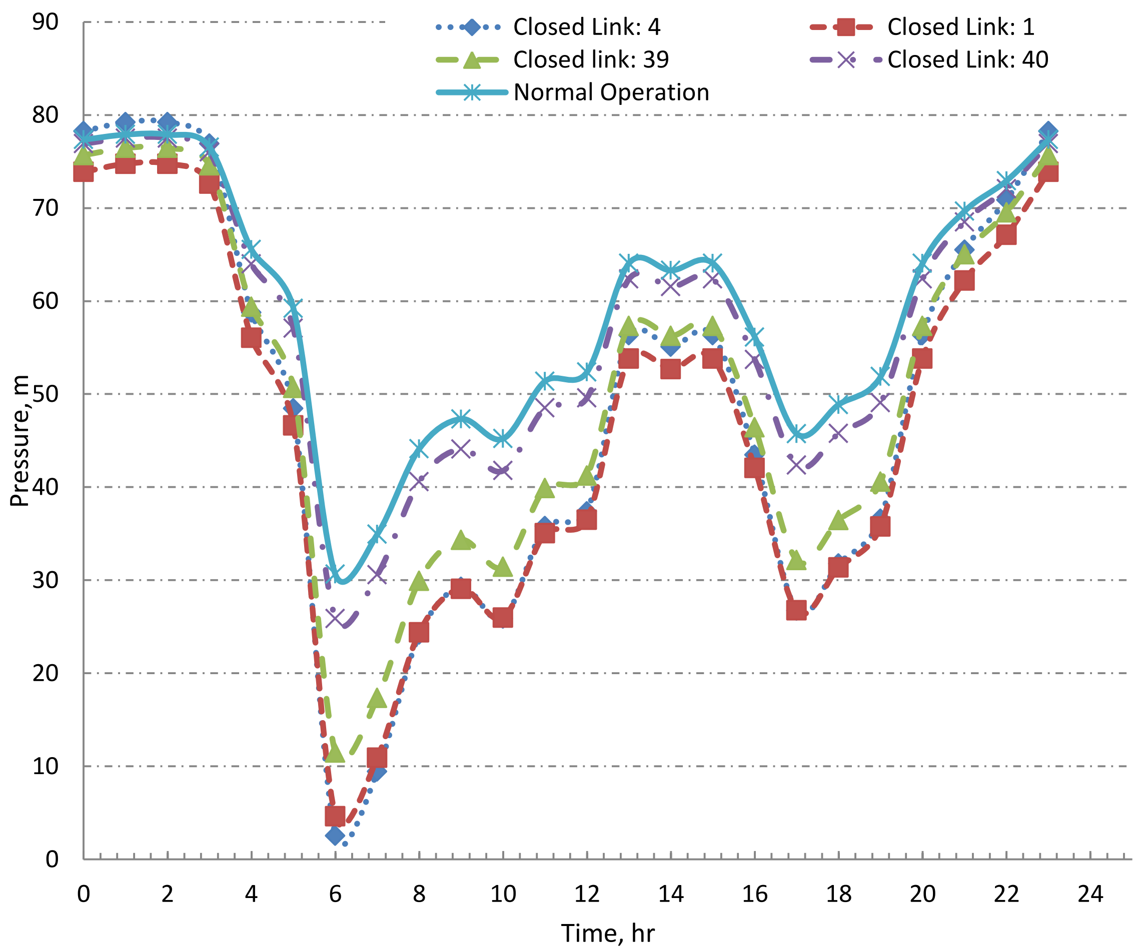


Figure 3.10: Available pressure at critical point under critical pipe failure condition

Table 3.7: EPS reliability results for Node 27 of the example network

| Time, hr. | Pressure, m | | | Demand, l/s | | Utility | | | Residual Chlorine, mg/l | | | Quality | | Combined | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Max. | Normal | Min. | Base | Available | Pressure | Demand | Belief | Max. | Normal | Min. | Utility | Belief | Utility | Belief |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| 0-2 | 79.60 | 78.41 | 77.16 | 19.75 | 19.75 | 1.00 | 1.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2-4 | 78.98 | 77.73 | 76.40 | 20.75 | 20.75 | 1.00 | 1.00 | 1.00 | 0.53 | 0.40 | 0.29 | 0.62 | 0.53 | 0.62 | 0.73 |
| 4-6 | 55.96 | 52.24 | 48.20 | 45.50 | 45.50 | 1.00 | 1.00 | 1.00 | 0.80 | 0.74 | 0.68 | 1.00 | 1.00 | 1.00 | 1.00 |
| 6-8 | 10.67 | 2.09 | -7.27 | 74.75 | 21.62 | 0.00 | 0.29 | 0.00 | 0.82 | 0.77 | 0.72 | 1.00 | 1.00 | 0.00 | 0.00 |
| 8-10 | 30.31 | 23.84 | 16.78 | 63.50 | 62.01 | 0.88 | 0.98 | 0.52 | 0.82 | 0.77 | 0.72 | 1.00 | 1.00 | 0.93 | 0.72 |
| 10-12 | 34.30 | 28.26 | 21.67 | 61.00 | 61.00 | 1.00 | 1.00 | 0.52 | 0.82 | 0.77 | 0.72 | 1.00 | 1.00 | 1.00 | 0.72 |
| 12-14 | 49.90 | 45.53 | 40.78 | 50.25 | 50.25 | 1.00 | 1.00 | 1.00 | 0.81 | 0.76 | 0.71 | 1.00 | 1.00 | 1.00 | 1.00 |
| 14-16 | 57.77 | 54.24 | 50.42 | 44.00 | 44.00 | 1.00 | 1.00 | 1.00 | 0.81 | 0.76 | 0.71 | 1.00 | 1.00 | 1.00 | 1.00 |
| 16-18 | 38.54 | 32.95 | 26.86 | 58.25 | 58.25 | 1.00 | 1.00 | 1.00 | 0.81 | 0.76 | 0.71 | 1.00 | 1.00 | 1.00 | 1.00 |
| 18-20 | 37.40 | 31.69 | 25.47 | 59.00 | 59.00 | 1.00 | 1.00 | 1.00 | 0.82 | 0.77 | 0.72 | 1.00 | 1.00 | 1.00 | 1.00 |
| 20-22 | 62.88 | 59.90 | 56.68 | 55.50 | 55.50 | 1.00 | 1.00 | 1.00 | 0.81 | 0.76 | 0.71 | 1.00 | 1.00 | 1.00 | 1.00 |
| 22-24 | 75.90 | 74.32 | 72.64 | 46.00 | 46.00 | 1.00 | 1.00 | 1.00 | 0.79 | 0.74 | 0.69 | 1.00 | 1.00 | 1.00 | 1.00 |

* In this case, the network has been simulated with zero initial quality because of modelling complexities. In a real WSS, such is not the case as the initial residual chlorine concentration will show up from the beginning of the simulation

Under critical failure conditions, the utilities have been based on the available pressure, available water volume, and available water quality; their beliefs have been estimated for all nodes individually and for the system as a whole. Table 3.7 shows the EPS reliability results for node 27. The estimated system utility and the belief of the calculated utility are 0.95 and 0.96 respectively. From Table 3.7, it is evident that the reliability for the first half of the day is not satisfactory, whereas the performance of the WSS during the second half of the day is excellent. The residual chlorine concentration takes about 3 hours to reach the critical node of the WSS, which causes a nearly zero water quality utility for the first few hours of the simulation. During the period of 6-8 h, the water demand is highest with an average maximum demand multiplier of 1.49 leading to an excessive pressure drop. However, the situation reverses during the second half of the day. The reduction of water demand and the availability of residual chlorine increase the utility parameters towards desired levels. Thereafter, it seems that both estimated utility and degree of belief reach 1, indicating the absolute reliability of the node.

### 3.5 Summary

This study proposes a reliability assessment methodology to estimate the overall reliability of a WSS. Reliability has been assessed in terms of consumer utilities received from a WSS in terms of available water pressure, volume and residual chlorine concentration and beliefs on the calculated utilities. The proposed methodology is general in nature and the traditional methodology can be interpreted as a subset. Using the methodology, a user can define an acceptable degree of uncertainty. If a user is interested in avoiding all uncertainties or wants to consider a predefined degree of uncertainty, the methodology provides a solution. Based on the methodology, a MATLAB program has been developed using the EPANET source code.

Note that EPANET is a demand dependent simulation engine that considers satisfied nodal demands irrespective of nodal pressure, which is not always the case in reality (Pathirana 2010). In reality, nodal flow will decrease with decreasing pressure. Therefore, a pressure-dependent simulation will be more suitable for simulating a network with low pressure or a network under deficit condition. In a pressure-dependent simulation, both nodal demands and pressure requirement have been considered simultaneously to obtain available flow which is more realistic to actual conditions. All the results can be calculated using a pressure-dependent simulation algorithm.

Although, the developed methodology has enormous potential for different engineering applications, including the field of oil, gas and electricity networks, the proposed methodology suffers by computational cost. For this study, the methodology has been demonstrated using a small network with 40 pipes and 27 nodes and only four independent parameters have been considered as uncertain parameters. However, in reality, most WSSs have hundreds of pipes and nodes which will create a computational burden, especially solution for water quality which has very small computational time steps. A better computation algorithm and parallel computing could increase the computational performance of the methodology which is something not addressed in this study. This study was especially focused on a novel integrated reliability of a WSS. However, integration of reliability, robustness and resilience (Zhang et al. 2012) of a WSS can be investigated in the future.

# CHAPTER 4 LEAKAGE POTENTIAL MODEL

A version of this chapter has been published in the Journal of Water Supply: Research and Technology – AQUA with the title "*Evaluating Leakage Potential in Water Distribution Systems: A Fuzzy-Based Methodology"* (Islam et al. 2012a).

## 4.1 Background

It is stated earlier that leakage from WDS is a universal problem around the globe-only the difference in volume. The latest global water supply and sanitation assessment report (WHO-UNICEF-WSSCC 2000) estimated that the typical value of non-revenue water in Africa, Asia, Latin America and Caribbean and in North America are 39%, 42%, 42% and 15% respectively. One of the main components of these is lost water through leakages (Farley and Trow 2003)

There is no single reason for occurrence of leakage in any WDS. There could be numerous physical, environmental and hydraulic factors that pose threats or make WDSs vulnerable for leakage. Different external (to the network) factors, network physical components, workmanship quality, network operating practices directly or indirectly influence the leakage. Among external factors, such as traffic loading, influences the pipe failure due to vibration and heavy loading over the buried pipes. Soil types and its permeability influence the leakage duration and flow rate. Groundwater table and temperature influence the moisture contents which may have potential impacts on the breakage and leakage (Farley 2001). Physical components like number of service connections, number of water meters, number of joints, material of the physical components, different types of demand and many other factors influence leakage significantly (Farley 2001; A. Lambert 2002; Tabesh et al. 2009). Factors like operating system pressure and the age of network (i.e., age of pipes and network components if they are not explicitly mentioned) increase the leakage rate (Fares and Zayed 2009). Similarly, the poor workmanship of different network components like meters, valves and pumps can be significant contributors to leakage in WDSs (Furness 2003).

To assess the effect of each factor on the leakage in WDSs, it is necessary to have a good monitoring system and huge amount of data. It is also necessary to have a well-established water leakage detection and management system which are quite uncommon in most of the small-sized WDSs, or even in many bigger systems in the developing countries. However, the utility managers of those communities always want to have the tools and techniques to understand the impacts of different factors on leakage and leakage potential (LP) of their distribution systems.

As mentioned in the literature review, there are significant numbers of studies (Fares and Zayed 2009; Jowitt and Xu 1993; Kleiner et al. 2004; Rogers and Grigg 2006; Sadiq et al. 2004; Yamini and Lence 2009) have also been reported in the literature that discussed the concepts related to WDS's reliability. However, most of these studies focus on the failure of the WDS integrity. Very little research has been reported for evaluating LP of any WDS. For example, Klusman (2002) proposed a methodology for evaluation of the LP in a carbon dioxide EOR[4]/sequestration project. However, no significant literature has been reported for evaluating LP for WDS.

This research employed the concept of risk to assess the leakage potential. As defined earlier, risk is a product of likelihood of an undesirable event, i.e., the probability of occurrence of the event, and its related consequences (Sadiq et al. 2004). The definition of consequence is a vague concept. There are numerous ways to model the consequence of any undesirable phenomenon. The consequence modelling is generally carried out in terms of socio-economic impact, human health loss, asset loss, and environmental impact (Arunraj and Maiti 2009). However, in this study, consequences have not been modelled rather only the likelihood or leakage 'potential' has been modelled. The scale of 'potential' is used as a continuous interval of [0 1] or [0 100%]. The terms 'probability', 'possibility', 'risk' and even 'likelihood' have been intentionally avoided to avert confusion. The term 'possibility' or 'likelihood' refers to *what can happen* whereas 'probability' refers to *what will happen*. Moreover, the terms 'possibility' and 'likelihood' have specific meanings in Bayesian theory and Possibility theory (Sadiq et al. 2010). But the essence of the term 'potential' is very similar to the 'possibility' or 'likelihood'. A 100% LP of a WDS means that the production volume and LP are same in that WDS. If 100% LP becomes effective to any WDS, then no water will be travelled to the tap of any consumer. Using the concepts of risk and fuzzy logic/fuzzy set theory, this research aims at developing a new tool for water utility managers for evaluating LP in different parts of WDS under limited data and resources. The tool will help them to prioritize their active leakage control (ALC) and rehabilitation strategies. The output of this model is a significant part of the developed integrated prognostic and diagnostic analysis framework.

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[4] Enhanced Oil Recovery (EOR) is a generic term used for expressing techniques for increasing the amount of crude oil that can be extracted from an oil field

It is important to note that the detectable pipe failure and leakage are not synonymous. All detectable failures are the subset of leakage, however, without any detectable failure a huge volume of background leakage can exist in any WDS. Considering their time of awareness, identification of their locations and time of repair, this kind of background leakage is the most important component of total leakage volume in any WDS (Farley 2001).

## 4.2 Leakage Potential Model Development Methodology

The proposed methodology requires identification of different leakage influencing factors and aggregation of those factors under varying operating system pressure. To aggregate the influences of each factor, a hierarchical relationship structure has been developed. Fuzzy rule-based (FRB) inferencing system has been used to aggregate the influences of each factor. To model the behavior of different influencing factors under varying operating system pressure, a pressure adjustment factor (PAF) has been developed and incorporated with the aggregation process.

### 4.2.1 Model Framework

Figure 4.1 shows the hierarchical structure of leakage influencing factors and their interrelationship. The structure consists of four levels or generations of factors. The LP is in the first generation whereas the basic contributory factors are either in the third or fourth generation. An extensive literature survey was carried out to identify these factors which contribute to the leakage in WDSs. Based on the literature survey (e.g., Fares and Zayed 2009; Farley 2001; Farley and Trow 2003; Lambert 2001; Lambert et al. 1999; May 1994) and state-of-the practice information, a list of 24 basic factors has been identified which directly (e.g., pressure) or /and indirectly (e.g., traffic movement) influences the leakage. The interrelationships among various basic and dummy factors have been expressed using Meta language developed by Sadiq et al. (2007, 2004). Each element of the hierarchical structure has been expressed as $X_{i,j}^{k}$ ,where, X represents the leakage influencing factors, *i* represents the child, *j* for parent and *k* denotes the generation of the basic influencing factors. Both basic (for which data can be obtained) and dummy or intermediate (derived based on basic factors) factors in a hierarchical structure are composed of a “parent” and “children” relationships. Factor with no parents is the total “LP for the system” and factors with no children are the basic leakage influencing factors.

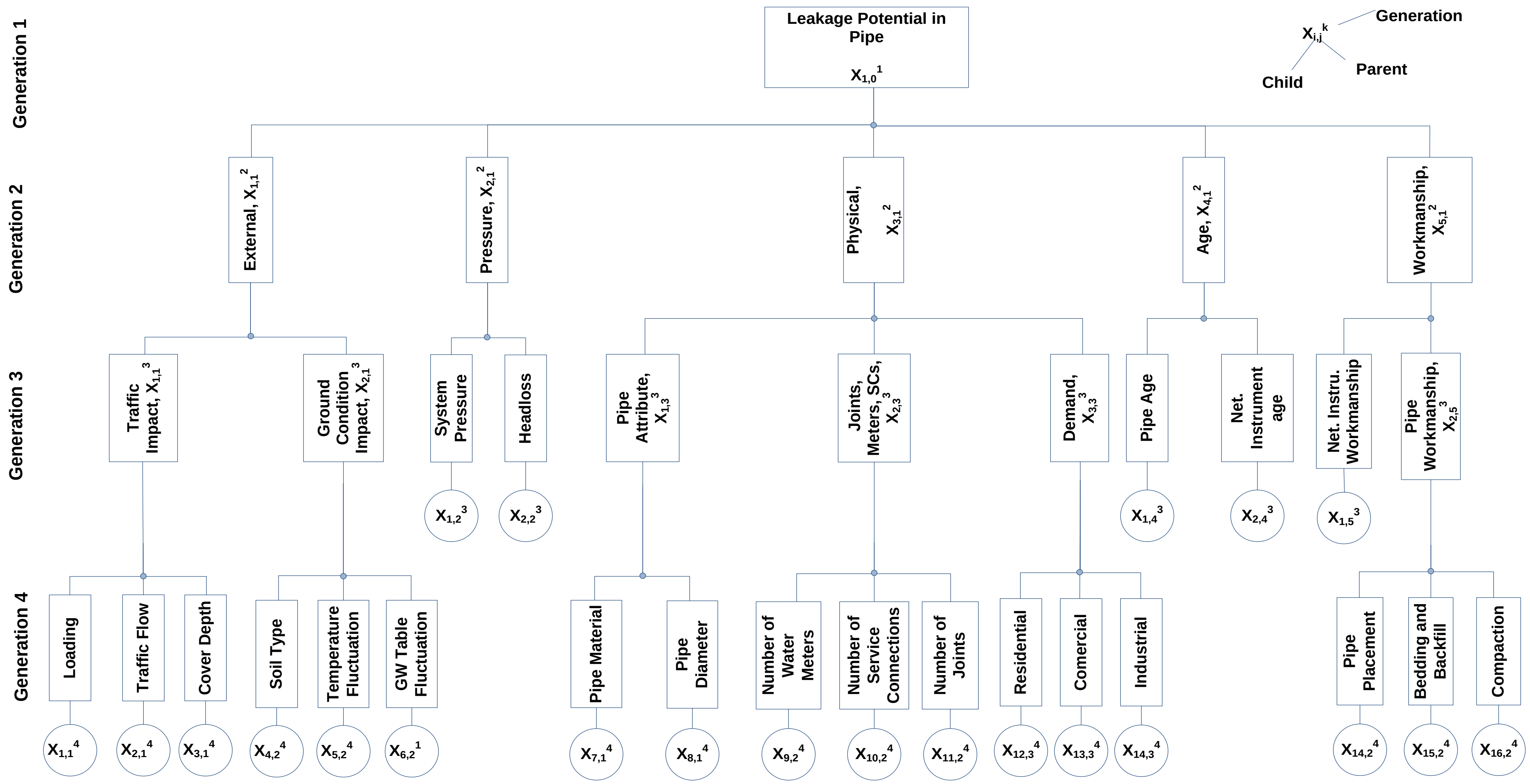



Figure 4.1: Hierarchical structure of selected leakage influencing factors

Among 24 factors, the influence of 22 basic factors, except pressure exponent[5] and reference pressure, can be propagated through these four generations. Pressure exponent and reference pressure influence LP taking part in the calculation of pressure adjustment factor provided in section 4.2.3. The first generation parent LP has five children in second generation namely external, pressure, physical, age and workmanship. Like their parent each of the five factors has their own children in the third generation. The parent factor “external” has two children namely traffic impact and ground condition impact. The parent factor “pressure” has two children namely system pressure and head loss which are basic factors. The parent factor “physical” has three children namely pipe attribute, joints, meters and service connections and demand. The parent factor “age” has two children namely pipe age and network instruments’ age which are basic factors. Network instrument workmanship and pipe workmanship are the children of workmanship; network instrument workmanship is a basic factor.

All third generation children except which are basic factors (children of age and pressure) have children in the fourth generation. Parent traffic impact has three basic children in fourth generation namely loading, traffic flow and cover depth. Similarly, the ground condition impact has three basic children: soil type, temperature fluctuation and groundwater table fluctuation. Pipe materials and pipe diameter are the children of pipe attribute while number of water meters, number of joints and number of service connections are the children of joints, meters and connections. Residential, commercial and industrial are three children of demand and finally pipe placement, bedding and backfill, and compaction are three children of pipe workmanship. All factors in the fourth generation are basic influencing factors.

After the development of LP framework, the research methodology is divided into two main parts; namely, fuzzy rule based (FRB) modelling and adjustment of pressure for calculating LP for varying operating system pressure profiles. In the first part of the methodology, FRB modelling has been carried out and in the second part, a pressure adjustment factor (PAF) has been calculated to model the influence of different factors under varying pressure conditions. Calculated PAF has been incorporated within FRB modelling by multiplying with the output of basic influence factors. Each part of the methodology has multiple stages. Details of the stages have been presented in the following sections. All stages have been implemented by using

[5] Leakage flow rate is proportional to a power (exponent) relationship of system pressure (Equation 4-19). The power (exponent) of the pressure of that relationship is termed as pressure exponent.

MATLAB 7.9 Fuzzy Inferencing Toolbox together with the MATLAB traditional coding environment (Fuzzy Logic Toolbox 2- User’s Guide 2011).

### 4.2.2 Fuzzy Rule Based (FRB) Modelling

Fuzzy sets are used to deal with vague and imprecise information (Zadeh 1965) . Fuzzy set theory is widely applied to solve real-life problems that are subjective, vague, and imprecise in nature (Smithson and Verkuilen 2006; Yang and Xu 2002). It provides a strict mathematical framework in which vague conceptual phenomena can be studied precisely and rigorously (Zimmermann 2001). Since its conceptualization, it has been used in various engineering applications including civil engineering. It is successfully implemented for the structural damage analysis, vibration control of flexible structure, cement rotary kiln, concrete analysis and design (Gad and Farooq 2001). Sadiq et al. (2007) implemented fuzzy logic for predicting water quality failures in WDS. There are numerous other examples for the application of fuzzy logic in water distribution modelling. Four steps are required to implement FRB modelling: fuzzification, inferencing, defuzzification and normalization (interpretation). Figure 4.2 shows the sequence of information flow for FRB modelling.

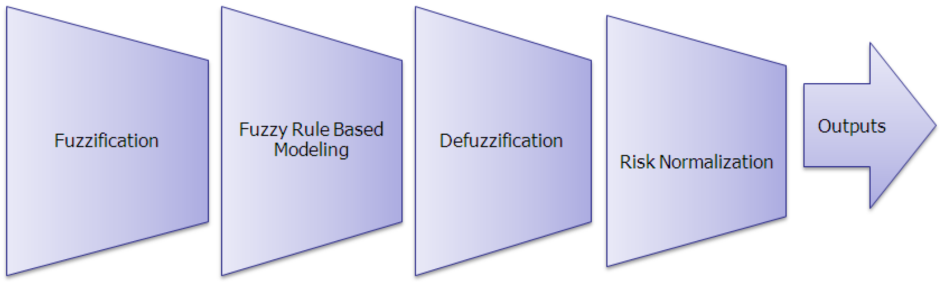
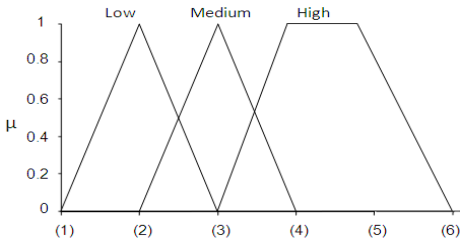


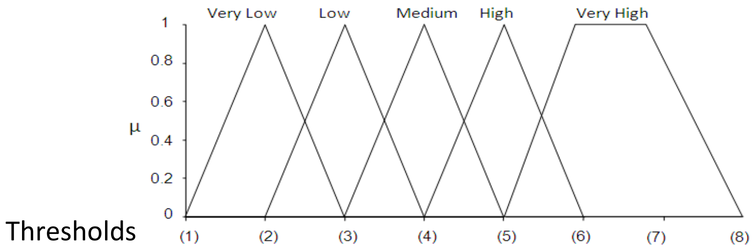

Figure 4.2: Information flow in FRB modelling

#### 4.2.2.1 Fuzzification

Fuzzification is a step that transforms all commensurate or non-commensurate data into a homogeneous scale by assigning memberships with respect to predefined linguistic variables (Chowdhury et al. 2007; Khan and Sadiq 2005).

Table 4.1: Fuzzy sets and linguistic definition of input parameters




Reference Figure: T1

Reference Figure: T2

| Inputs | Symbol | Interval | Ref. Fig. | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| LD | $X_{1,1}^{4}$ | 0-300 | T1 | 0 | 0 | 150 | 300 | 300 | 300 | | |
| FL | $X_{2,1}^{4}$ | 0-30000 | T1 | 0 | 0 | 15000 | 30000 | 30000 | 30000 | | |
| CD[6] | $X_{3,1}^{4}$ | 5-0 | T1 | 0 | 0 | 0.9 | 2 | 5 | 5 | | |
| ST[7] | $X_{4,2}^{4}$ | 0-100 | T1 | 0 | 0 | 30 | 60 | 100 | 100 | | |
| TF | $X_{5,2}^{4}$ | 0-20 | T1 | 0 | 0 | 6 | 12 | 20 | 20 | | |
| GF | $X_{6,2}^{1}$ | 0-10 | T1 | 0 | 0 | 3 | 6 | 10 | 10 | | |
| NM | $X_{9,2}^{4}$ | 0-100 | T1 | 0 | 0 | 30 | 60 | 100 | 100 | | |
| NS | $X_{10,2}^{4}$ | 0-100 | T1 | 0 | 0 | 30 | 60 | 100 | 100 | | |
| NJ | $X_{11,2}^{4}$ | 0-50 | T1 | 0 | 0 | 15 | 30 | 50 | 50 | | |
| RD[8] | $X_{12,3}^{4}$ | 0-1 | T1 | 0 | 0 | 0.5 | 1 | 1 | 1 | | |
| CoD | $X_{13,3}^{4}$ | 0-1 | T1 | 0 | 0 | 0.5 | 1 | 1 | 1 | | |
| InD | $X_{14,3}^{4}$ | 0-1 | T1 | 0 | 0 | 0.5 | 1 | 1 | 1 | | |
| PP[9] | $X_{14,2}^{4}$ | 0-1 | T1 | 0 | 0 | 0.5 | 1 | 1 | 1 | | |
| BB | $X_{15,2}^{4}$ | 0-1 | T1 | 0 | 0 | 0.5 | 1 | 1 | 1 | | |
| C | $X_{16,2}^{4}$ | 0-1 | T1 | 0 | 0 | 0.5 | 1 | 1 | 1 | | |
| PM[10] | $X_{7,1}^{4}$ | 0-1 | T1 | 0 | 0 | 0.5 | 1 | 1 | 1 | | |
| PD | $X_{8,1}^{4}$ | 0-10 | T1 | 0 | 0 | 0.3 | 0.72 | 10 | 10 | | |
| SP | $X_{1,2}^{3}$ | 0-100 | T2 | 0 | 0 | 25 | 50 | 75 | 100 | 100 | 100 |
| HL | $X_{2,2}^{3}$ | 2-0 | T1 | 0 | 0 | 0.25 | 0.5 | 2 | 2 | | |
| PA | $X_{1,4}^{3}$ | 0-100 | T2 | 0 | 0 | 25 | 50 | 75 | 100 | 100 | 100 |
| IA | $X_{2,4}^{3}$ | 0-100 | T2 | 0 | 0 | 25 | 50 | 75 | 100 | 100 | 100 |

LD=Traffic loading (KN); FL= Traffic flow (Vehicle/h); CD=Cover depth (m); ST=Soil Type (% finer); TF= Temperature fluctuation ($^0$C); GF=Ground water table fluctuation (m); NM=(Number of )water meters; NS= (Number of )service connection; NJ= (Number of) joints; RD=Residential demand; InD=Industrial demand; CoD=Commercial demand; PP= (Quality of) pipe placement; BB= (Quality of) bedding and backfills; C=Quality of compaction; PM= Pipe materials; PD=Pipe diameter (m); SP=System pressure, m; HL=Head loss (m/km); PA= Pipe age (yr)IA= Network instrument age( yr).

[6] Cover depth and head loss has reverse relationship with LP. Therefore, in Figure T1 the 'Low' should be read as the 'High' and the 'High' should be read as the 'Low')

[7] Soil type defined by percentage finer than 0.002 mm

[8] All the demands are relative to pressure drop. If pressure drop due to demand is high, then demand is consider as a high value and vice versa

[9] Low placement quality considered when pipe placement is carried out by unskilled technicians with no engineering supervision and high placement quality when placement is carried out by skilled technician with engineering supervision. Same is considered for Bedding and Backfills and for Compaction.

[10] Assumed low value for metallic (DI, ST,GI, CI etc.) pipes, medium value for plastic (HDPE, PE, PVC etc.) pipes and high value for others(PC, AC, etc.) pipe materials

To fuzzify data, generally triangular fuzzy numbers (TFN) or trapezoidal fuzzy numbers (ZFN) are used to represent linguistic variables (Lee 1996). For this study, all the leakage influencing factors have been modelled using TFN and ZFN (Figure 3.4). Equations 3.2 and 3.3 (Chapter 3) have been used to model the TFN and ZFN.

Definitions of a, b, c, d for different leakage influencing factors in different granularity levels have been presented in the form of thresholds shown in Figure T1 and T2 attached with the Table 4.1. To define fuzzy numbers, threshold values need to be read based on the values defined in Table 4.1. For each ZFN, first, second, third and fourth values are a, b, c, and d respectively. However, for TFN, the fourth value is out of consideration. For each leakage influencing input, type of fuzzy number and threshold values (eventually, a, b, c and d) are based on the literature review (e.g., Fares and Zayed 2009; Farley 2001; Farley and Trow 2003; Lambert 2001; Lambert et al. 1999; May 1994) and expert opinions from water industry.

Most of the membership functions have three levels of granularity which are expressed through linguistic variables: *low*, *medium* and *high*. However, for some relatively more sensitive input factors and their output (e.g., pressure, age), 5-level granularity for membership functions (*very low*, *low*, *medium*, *high* and *very high*) is defined (Figure 4.3). The final LP output function has also 5-level of granularity. For example, Figure 4.3 shows a fuzzified value of pressure 45m with the following degree of memberships ($\mu_x$): very low (0), low (0.2), medium (0.78), high (0) and very high (0).

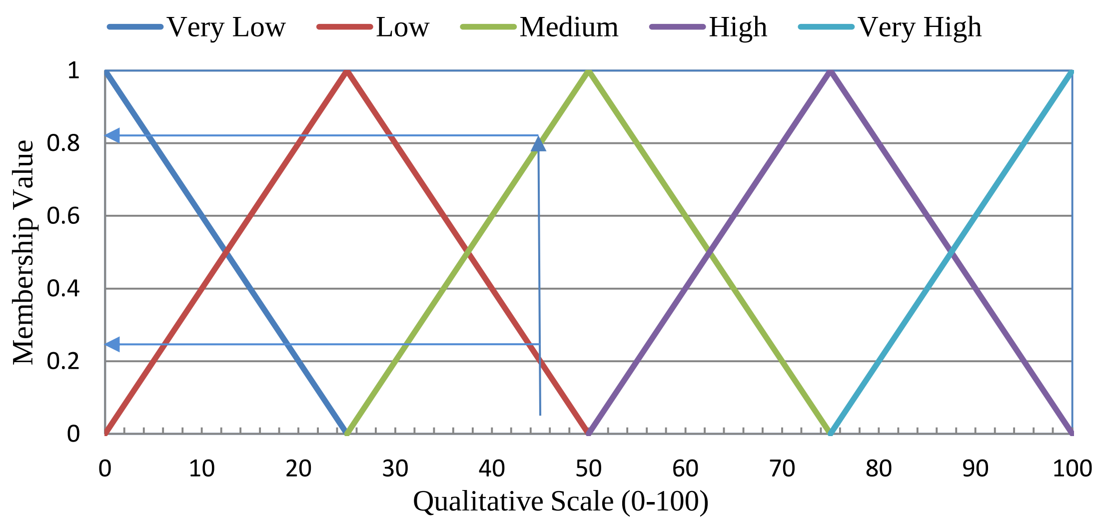



Figure 4.3: Five level granularity of fuzzy numbers

#### 4.2.2.2 Fuzzy Inferencing System

In FRB modelling, the relationships between fuzzy variables are represented by if-then rules in the form "**If** antecedent proposition **then** consequent proposition". In a linguistic model where both the antecedent and consequent are fuzzy propositions, the rule can be written as (Mamdani, 1997):

$$\mathbf{R}_i: \quad \textbf{If } x \text{ is } A_i \textbf{ then } y \text{ is } B_i; \quad i = 1, 2, \ldots, k \qquad [4.1]$$

where, $A_i$ and $B_i$ are linguistic constants and the antecedent $x$ (input) and the consequent $y$ (output) are linguistic variables. The values of $A_i$ and $B_i$ are selected from sets of prescribed terms and the values of $x$ and $y$ belong to fuzzy sets in their respective domains. The rule $\boldsymbol{R} = \{\boldsymbol{R_i}/i = 1, 2, \ldots, k\}$ and the sets $A$ and $B$ constitute the knowledge base of the linguistic model. A fuzzy rule provides a restriction on the simultaneous occurrence of $x$ and $y$; $\boldsymbol{R}_\mathbf{i}\ (X \times Y) \rightarrow [0, 1]$. The fuzzy conjunction $A_i \wedge B_i$ can be computed using a *t-norm* operator (*minimum*) as follows (Mamdani, 1997):

$$\boldsymbol{R_i} = A_i \times B_i \quad \text{i.e.,} \quad \mu_{Ri}\ (x, y) = \mu_{Ai}\ (x) \wedge \mu_{Bi}\ (y) \qquad [4.2]$$

The minimum operator is computed on the Cartesian $X$-$Y$ product space for all possible pairs of $x$ and $y$. The fuzzy relation $\boldsymbol{R}$ represents the entire model and is given by the disjunction (*union or maximum*, i.e., *s-norm*) of $k$ individual relations of the $\boldsymbol{R_i}$ rule, as follows:

$$\boldsymbol{R} = \bigcup_{i=1}^{k} R_i, i.e., \mu_R(x, y) = \max_{1 \le i \le k}\left[\mu_{Ai}(x) \wedge \mu_{Bi}(y)\right] \qquad [4.3]$$

The fuzzy relation $\boldsymbol{R}$ encrypts the entire rule-base and allows computation of the model output using the max-min composition ($^{o}$) according to the following equation:

$$y = x\ ^{o}\ \boldsymbol{R} \qquad [4.4]$$

For an input fuzzy value $x = A'$, an output value $B'$ is given by the following composition:

$$\mu_{B'}(y) = \max_{X}\left[\mu_{A'}(x) \wedge \mu_R(x, y)\right] \qquad [4.5]$$

Substituting $\mu_R$ (x, y) from Equation 4.5, the above expression takes the following form:

$$\mu_{B'}(y) = \max_X(\mu_{A'}(x) \wedge \max_{1\le i\le k}[\mu_{Ai}(x) \wedge \mu_{Bi}(y)]) \qquad [4.6]$$

The above equation is rearranged as follows:

$$\mu_{B'}(y) = \max_{1\le i\le k}(\max_X[\mu_{A'}(x) \wedge \mu_{Ai}(x)] \wedge \mu_{Bi}(y)) \qquad [4.7]$$

Assuming $\beta_i = \max_X[\mu_{A'}(x) \wedge \mu_{Ai}(x)]$ is the degree of fulfillment of the $i^{th}$ rule antecedent. The resulting output fuzzy set of the linguistic model is of the following form:

$$\mu_{B'}(y) = \max_{1\le i\le k}[\beta_i \wedge \mu_{Bi}(y)], \quad y \in Y \qquad [4.8]$$

Defuzzification of fuzzy set elements can be implemented using quality ordered weights ($w_l$) to obtain a crisp output. Defuzzification is conducted using Equation 4.9 (Yang and Xu 2002) where $m$ is the number of output granules, $\mu_{B'l}(y)$ is the output membership for each output granule (Equation 4.8), and $B_o^l$ is the crisp representative value of each output granule:

$$y_O = \sum_{l=1}^{m} \mu_{B'l}(y) \times B_O^l \times w_l \qquad [4.9]$$

Details on defuzzification have been described in next section of this article. The fuzzy rule-based model is trained (fine-tuned) using linear optimization of an objective function $\min\left(\sqrt{Avg(y_{obs} - y_O)^2}\right)$, which is a minimization of the square root of the mean square error (**SRMSE**), where $y_{obs}$ is the observed value, $y_o$ is the modeled value (Equation 4.9).

The above algorithm is known as a single-input single-output (SISO) model. The algorithm could be extended to a multiple-input single-output (MISO) model as follows:

***R_i***: **If** $x_1$ is $A_{1i}$ **and** $x_2$ is $A_{2i}$ **and**…**and** $x_p$ is $A_{pi}$ **then** $y$ is $B_i$; $i = 1, 2, .., k$ [4.10]

The Equation 4.10 is a special case of Equation 4.1, where the set $A_i$ is obtained by the Cartesian product of fuzzy sets $A_i = A_{1i} \times A_{2i} \times A_{3i} \times ... \times A_{pi}$ and the degree of fulfillment ($\beta_i$) becomes:

$$\beta_i = \mu_{A1i}(x_1) \wedge \mu_{A2i}(x_2) \wedge ... \wedge \mu_{Api}(x_p); \qquad i = 1, 2, .., k \qquad [4.11]$$

Successive details are identical to those of SISO (Yager and Filev 1994) model. Two fuzzy rule-based inferencing methods are very common: the Mamdani and the Takagi, Sugeno and Kang (TSK) methods. The Mamdani method is the most popular in practice and connects antecedents to consequents through a rule set, whereas the TSK method provides a systematic approach to generating fuzzy rules from an input-output function (Ross 2004).

For the present study, Mamdani algorithm has been implemented. This algorithm was proposed by Mamdani and Assilian (Ross 2004). In this methodology, the MISO model has been used as form of:

**$R_i$: If** $x_1$ is $A_{1i}$ **and** $x_2$ is $A_{2i}$ **and**…**and** $x_{pi}$ is $A_{pi}$ **then** $y_i$ is $B_i$; i = 1, 2, ..., $k$ [4.12]

where $A_{1i}$, $A_{2i}$, ... $A_{pi}$ are the fuzzy set representing the $i^{th}$ antecedent vector-values, and $B_i$ is the fuzzy set representing the $i^{th}$ consequent.

In the Mamdani and Assilian max-product inference, the degree of fulfillment ($\beta_i$) and the aggregated output for the $k$ rules ($\mu_{Bi}$ □($y$), are estimated by following two equations respectively:

$$\beta_i = min\,[\mu_{A1i}\ (x_1),\ \mu_{A2i}\ (x_2),\ldots,\ \mu_{Api}\ (x_p)] \qquad [4.13]$$

$$\mu_{Bi}\ (y) = \max_i\ [min\,[\mu_{A1i}\ (x_1),\ \mu_{A2i}\ (x_2),\ldots,\ \mu_{Api}\ (x_p)]] \ ; \ i = 1, 2, \ldots k \qquad [4.14]$$

#### 4.2.2.3 Defuzzification

Defuzzification is a procedure for determining the crisp value which is considered the most representative of the fuzzy set output taken as an isolated entity (Saade and Diab 2002). Several methods of defuzzification exist, e.g., the centre of gravity (COG), bisector, mean of maximum, smallest of maximum and largest of maximum. COG technique is the most popular due to its simplicity and easiness for programming, less use of computer resource and a reasonable output

(Fares and Zayed 2009). Therefore, this study also applies COG method. The value of the crisp LP value has been calculated following the equation:

$$Crisp\ LP = \frac{\sum_{1}^{k} Ar^k Dc^k}{\sum_{1}^{k} Ar^k} \qquad [4.15]$$

where, $A_r$ is the truncated area taken from membership function based on inferencing rules, $D_c^k$ is the moment arm of the truncated area and $k$ is the membership function.

#### 4.2.2.4 Normalization

For absolute favorable condition, the calculated LP should be close to zero and for absolute unfavorable condition the calculated LP should be close to the unit value. However, by using COG method, it is impossible to obtain these two extreme values due to the nature of the approximation. Therefore, produced results using this method could be confusing to the people who are not familiar with the method. To avoid this confusion and to make easier interpretation of the results, the calculated crisp value has been normalized between 0 and 1 by using Equation 4.16:

$$LP_N = \frac{LP^{cog} - LP^{cog}_{min}}{LP^{cog}_{max} - LP^{cog}_{min}} \qquad [4.16]$$

where $LP_N$ is the normalized LP for any condition; $LP^{cog}$ is the LP for any condition calculated by COG method; $LP^{cog}_{min}$ is the minimum LP for extreme favorable condition calculated by COG method; and $LP^{cog}_{max}$ is the maximum LP for extreme unfavorable condition calculated by COG method.

### 4.2.3 Pressure Adjustment

Pressure is the most important factor that influences the leakage flow rates (Farley 2001). It also affects other leakage influencing basic factors ( Farley 2001; Farley and Trow 2003; Lambert 2001). To model the relationship between pressure and other influencing factors, a pressure adjustment factor (PAF) has been proposed to reflect the influence of pressure to all pressure dependent basic inputs. If $\rho_G^{G-1}$ is the outputs for the influencing factors of the generation $G^{th}$, $\rho_G^{G-1}$ will serve as input for the upper generation, i.e. generation $G^{th-1}$. The proposed PAF has been applied to the outputs ($\rho_G^{G\text{-}1}$) under the condition of ($\rho_G^{G\text{-}1}$) × PAF ≤ 1. Then the influence of pressure will be propagated to the final crisp LP according to the structure earlier provided in Figure 4.1.

There are four main steps to calculate the proposed PAF. Firstly, it is necessary to select the "reference system pressure". The term "reference system pressure" is the pressure above which leakage and break frequency increases more rapidly. At this level, pressure initiates to influence the other leakage influencing factors. For a system with continuous supply, leakage and break frequency increases rapidly when pressure exceeds around 35 to 40 meters (50 to 57.1 psi) of head (Lambert, 2001; Farley and Trow, 2003). Therefore a reference system pressure could be between 35 m to 40 m (50 to 57.1 psi) of head. However, the value of reference system pressure could change based on the network condition, age of network, design standards and other factors.

After selection of reference system pressure, it is necessary to select the average operating system pressure. If the proposed model is intended to apply to an individual pipe, the average operating system pressure should be calculated as an average of upstream and downstream pressure of the pipe. However, if the model intended to apply to a whole or part of WDS, then average operating system pressure should be selected in such a way that it represents the average operating system pressure of the whole or part of WDS, respectively.

Third, it is necessary to estimate the pressure exponent ($N1$) which generally varies between 0.50 and 2.50, depending upon the type of leakage path, network age, corrosion, materials and other network related factors (Farley and Trow 2003). However, maximum values in excess of 2.5 reported in field tests (Farley and Trow 2003) are also realistic (Greyvenstein and Van Zyl 2007). For larger detectable leakage from plastic pipes, typical $N1$ value could be 1.5 or even higher, while larger detectable leakages in the metal pipe could have $N1$ value close to 0.5 (Lambert 2001). Greyvenstein and Van Zyl (2007) found a value of pressure exponent 2.3 in a steel pipe with extensive corrosion damage to the pipe wall and having reduced supporting material surrounding the leak openings.

Finally, this research developed a special FRB model based on the approach discussed in the section 4.2.2. For this special model, pressure is considered only influencing factor and hence defined rules for this model is only pressure dependent (SISO model). For example, if pressure is *low* then LP is *low*; if pressure is *high* then LP is *hig*h. Figure 4.4 shows the LP model considering pressure as the only influencing factor.

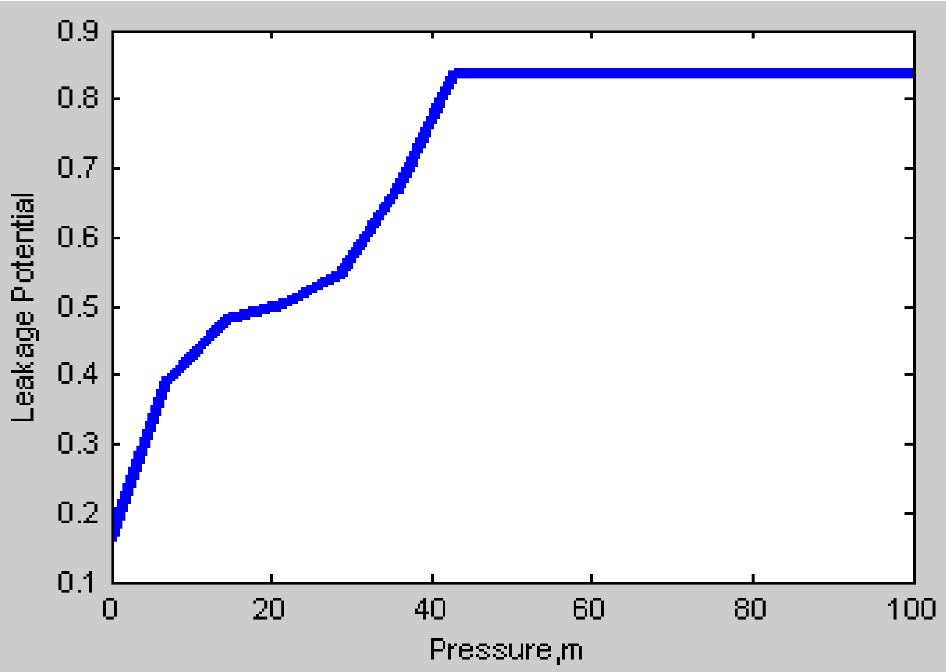



Figure 4.4: LP evaluation considering only the pressure as an influencing factor

The model has been then used to determine LP for estimated reference system pressure (LPRP) and LP for estimated operating system pressure (LPSP). Based on estimated LPRP, LPSP and the pressure exponent $N1$, PAF is calculated by using Equation 4.17:

$$PAF = \left(\frac{LPSP}{LPRP}\right)^{N1} \quad [4.17]$$

The relationship of Equation 4.17 is based on the general relationship between pressure and leakage. According to Lambert (2001) the appropriate relationship between leakage and pressure can be expressed by following two equations

$$L \propto P^{N1} \quad [4.18]$$

$$\frac{L1}{L0} = \left(\frac{P1}{P0}\right)^{N1} \quad [4.19]$$

where $L$ represents the leakage volume per unit time, $P$ represents the pressure, $P_0$ is the reference system pressure, $L_0$ is the leakage rate for the reference system pressure, $P_1$ is the system pressure at any time, $L_1$ is the system leakage for Pressure $P_1$ and $N1$ is the pressure exponent.

## 4.3 Example Evaluation of Leakage Potential

To demonstrate the actual process of the developed model as described previously, an example evaluation process has been described below. The example shows, how the different inputs contributed to the overall leakage potential evaluation.

**Step 1**: Hierarchical model (Figure 4.1)

**Step 2**: Data collection (Table **4.3**)

**Step 3**: Calculation of pressure adjustment factor (PAF[11]):

From Table **4.3**, Operating system pressure (SP) =12.56 m (17.94 psi); Reference pressure (RP) = 25 m (35.71 psi) and N = 1.16. For SP<RP, no influence of pressure to other factors is considered. Therefore PAF = 1.

However, for demonstration purpose, calculation of PAF for SP = 35 m (50 psi) where SP>RP has been shown as follow:

**Step 3.1**: Input and output fuzzy membership function for pressure dependent SISO model (Figure 4.5)

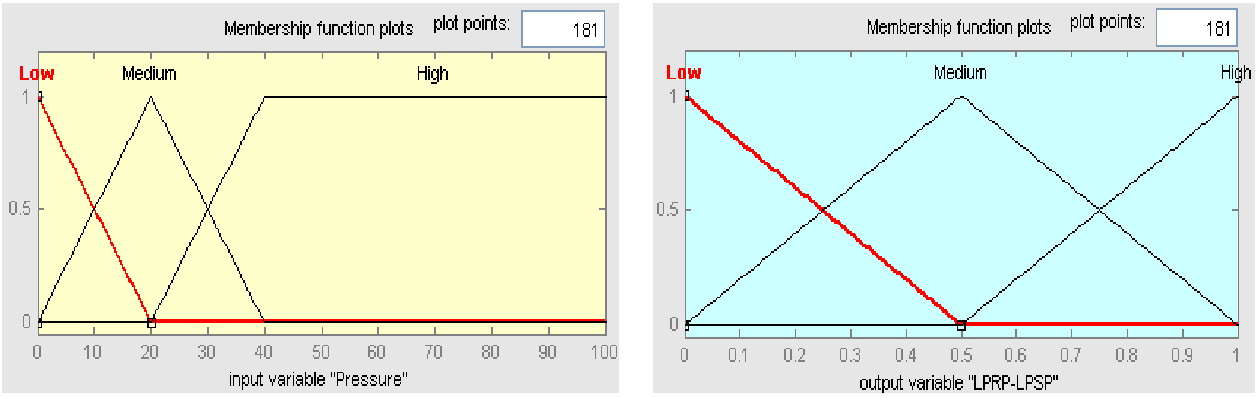



Figure 4.5: Input and output fuzzy membership functions for pressure dependent SISO model

[11] For all abbreviation please read main thesis

**Step 3.2**: Rules for pressure dependent SISO model

$R_1$: If pressure is *low* then LPRP-LPSP[12] is *low*)

$R_2$: If pressure is medium then LPRP-LPSP is *medium*

$R_3$: If pressure is *high* then LPRP-LPSP is *high*

**Step 3.3**: Rule evaluation and outputs (Figure 4.6)

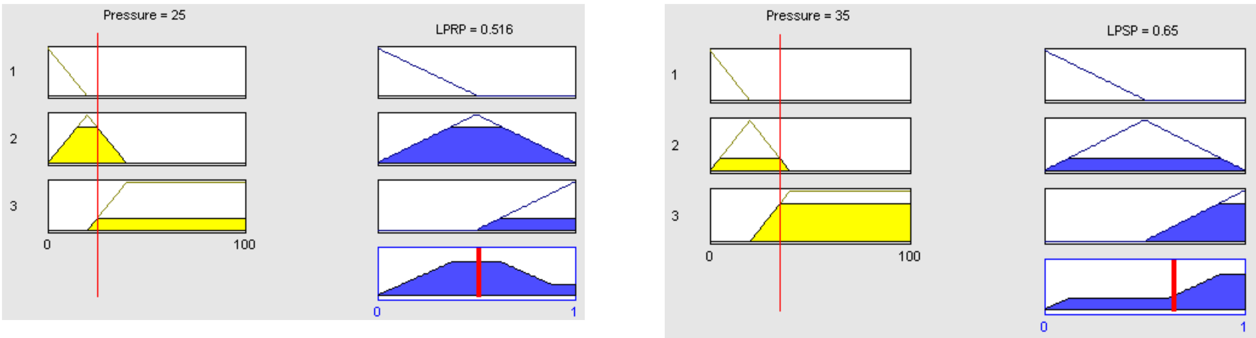



Figure 4.6: Rules evaluation and outputs for RP and SP

**Step 3.4**: PAF calculation

Defuzzified output for RP (LPRP) = 0.516 and Defuzzified output for SP (LPSP) = 0.65.

Therefore PAF $= \left(\frac{\text{LPSP}}{\text{LPRP}}\right)^{\text{N1}} = \left(\frac{0.650}{0.513}\right)^{1.16} = 1.32$

**Step 4**: Fuzzification of basic inputs

There are 24 basic factors (22 factors are fuzzified and 2 factors are incorporated with PAF). Only for demonstration purpose, inputs for Joints, Meters, SCs ($X_{2,3}{}^{3}$) group has been shown.

**Step 4.1**: Input and output membership function for Pressure only SISO model

[12] Evaluate LPRP when input variable is reference pressure (RP) and evaluate LPSP when input variable is operating system pressure (SP)

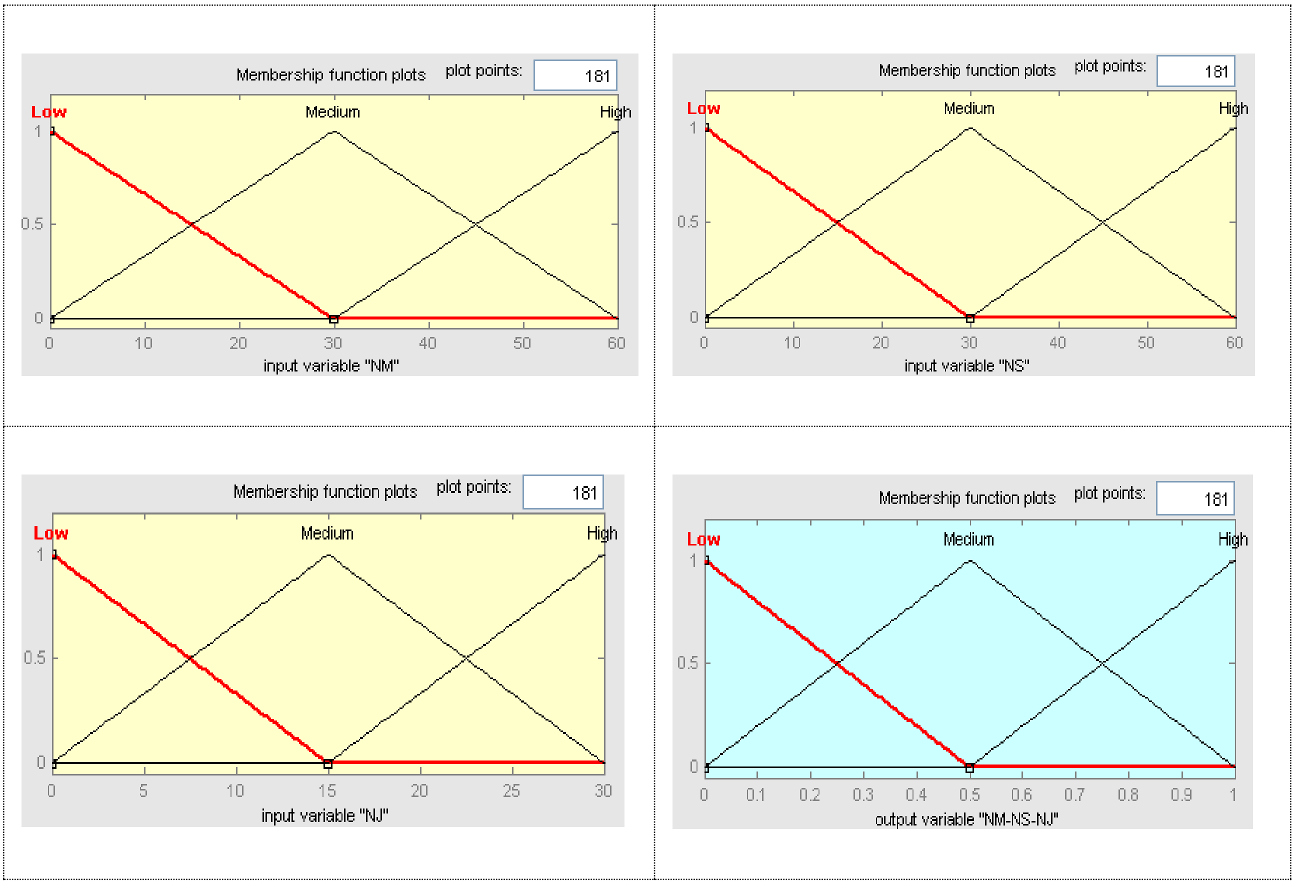



Figure 4.7: Input and output membership function for MISO model

**Step 4.2**: Rules for MISO model (Figure 4.7)

$R_1$: If NM is *low* and NS is *low* and NJ is *low* then NM-NS-NJ is *low*

$R_2$: If (NM *low*) and (NS *low*) and (NJ *medium*) then (NM-NS-NJ is *low*)

$R_3$: If (NM *low*) and (NS *low*) and (NJ *high*) then (NM-NS-NJ is *medium*)

.......................................................................................................

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$R_{26}$: If (NM *high*) and (NS *high*) and (NJ *medium*) then (NM-NS-NJ is *low*)

$R_{27}$: If (NM *high*) and (NS *high*) and (NJ *high*) then (NM-NS-NJ is *high*)

**Step 4.3**: Rule evaluation and outputs (Figure 4.8)

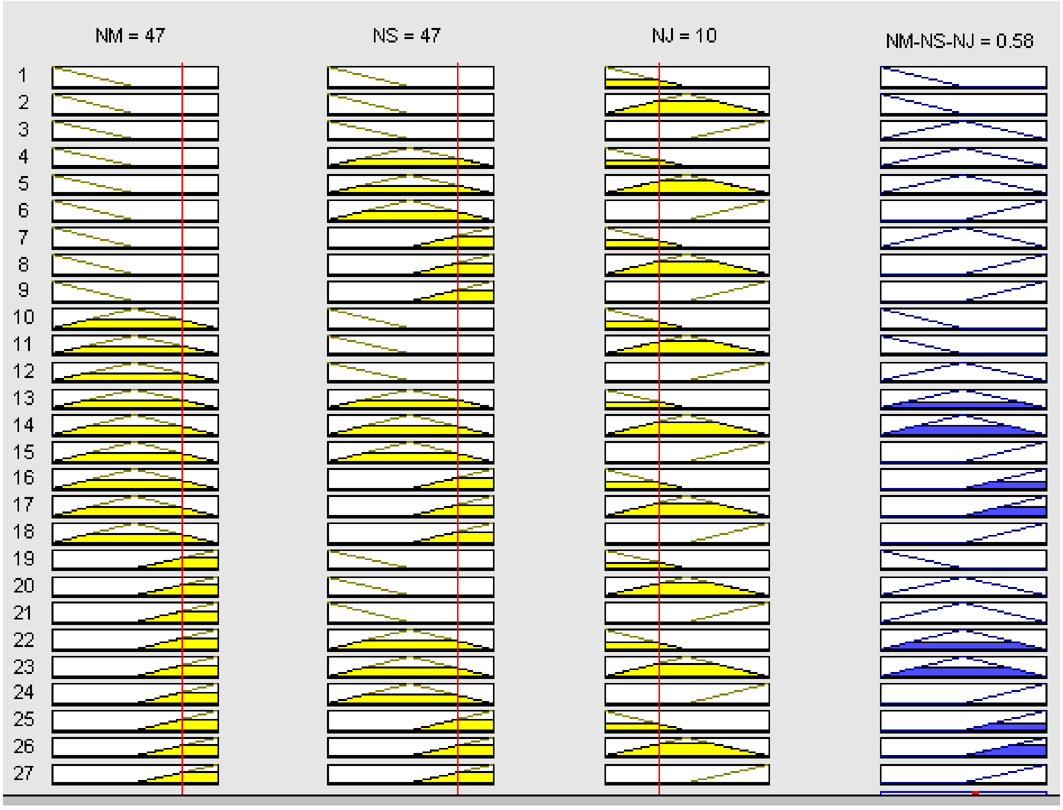



Figure 4.8: Rules evaluation and outputs for NM, NS and NJ

Defuzzified output from pressure independent NM, NS and NJ= 0.58

**Step 4.4**: Normalization

Maximum impact for extreme unfavorable conditions from NM, NS and NJ without normalization using COG method: 0.837.Minimum impact for extreme favorable conditions from NM, NS and NJ without normalization using COG method: 0.1633

Therefore, normalized impact: $R_N = \frac{R^{cog}-R^{cog}_{min}}{R^{cog}_{max}-R^{cog}_{min}} = \frac{0.58-0.163}{0.837-0.163} = 0.619$

**Step 4.5**: Incorporation of PAF

Pressure dependent input in third generation as Joints, Meters, SCs ($X_{2,3}^{3}$) = 0.619×PAF = 0.619×1 = 0.58[13].

[13] If( $X_{2,3}^{3}$ )×PAF>1 then assumed $X_{2,3}^{3}$ = 1.

**Step 5**: Steps 4 has been repeated for other fourth generation inputs. Resulting third generation dummy inputs for traffic impact ($X_{1,1}^3$), ground condition impact ($X_{2,1}^3$), pipe attribute ($X_{1,3}^3$), demand ($X_{3,3}^3$), pipe workmanship ($X_{2,5}^3$) and joints, meters, SCs ($X_{2,3}^3$) are 0.444, 0.333, 0.484, 0.517 , 0.551 and 0.58 respectively. In the generation, there are four basic inputs which are system pressure (SP), head loss (HL), pipe age (PA) and network instrument age (IA). The values of these basic inputs are obtained from Table 4.2.

**Step 6**: Using inputs obtained in step 5, FRB inferencing has been carried out. The output obtained for the generation $G^{th}$ ($3^{rd}$ generation for example) will be the input for the generation $G^{th-1}$ (i.e., $2^{nd}$ generation). Resulting second generation dummy inputs for external ($X_{1,1}^2$), pressure ($X_{2,1}^2$) , physical ( $X_{3,1}^2$), age( $X_{4,1}^2$), workmanship($X_{5,1}^2$) are 0.494, 0.147,0.587,0.202 and 0.493 respectively. It is noted that in this case no pressure adjustment has been carried out except for age. However, normalization has been carried out as step 4.4.

**Step 7**: Using dummy inputs obtained in Step 6, FRB inferencing has been carried out to estimate final normalized crisp value of leakage potential (LP). For this case, dummy inputs obtained in Step 6 have been fuzzified using TFN. Dummy parameters external ($X_{1,1}^2$), physical($X_{3,1}^2$) have two levels of granularity (i.e., low and high) and age( $X_{4,1}^2$), workmanship($X_{5,1}^2$) and pressure ($X_{2,1}^2$) have three level of granularity (i.e., low, medium and high). However, the output final LP has five level of granularity (i.e., very low, low, medium, high and very high). Number of rules applied for this part of modelling is 108 (3×3×3×2×2). Typical rules used are shown as following:

> $R_1$: If External is *low* and Physical is *low* and Workmanship is *low* and Pressure is *low* and Age is *low* then LP is *low*
>
> ..........................................................................................................................
>
> ..........................................................................................................................
>
> $R_{107}$: If External is *high* and Physical is *high* and Workmanship is *high* and Pressure is *high* and Age is *medium* then LP is *high*
>
> $R_{108}$: If External is *high* and Physical is *high* and Workmanship is *high* and Pressure is *high* and Age is *high* then LP is *very high*

Using this FRB model estimated leakage potential before normalization is 0.484. This defuzzified has been normalized similar as step 4.4. However, for this case, maximum impact for extreme unfavorable conditions from external, physical, workmanship, pressure and age without normalization using COG method: 0.92 and Minimum impact for extreme favorable conditions from external, physical, workmanship, pressure and age without normalization using COG method: 0.08.

Normalized leakage potential: $LP_N = \frac{R^{cog} - R^{cog}_{min}}{R^{cog}_{max} - R^{cog}_{min}} = \frac{0.484-0.08}{0.92-0.08} = 0.48075$

Therefore, final normalized crisp value of leakage potential (LP) is 0.481 or 48%.

## 4.4 Application of Proposed Leakage Potential Model

This study proposed a model that can be implemented to an individual pipe, or to a part of the network or to the whole WDS. The extent of application depends on the degree of accuracy required for a particular case and spatial variability of the influencing factors. If the spatial variability of different leakage influencing factors is very high, developed model should be implemented in each pipe of the network. In this case, all the network instruments (i.e., joints, service connections, water meters, fixtures, fittings, etc.) located on the pipe are needed to be considered as a part of the pipe. A special attention should be given to avoid duplication of any network instrument. Each pipe will have a separate LP and those can be presented as LP map of the WDS. However, if the spatial variability of different leakage influencing factors is relatively small, the developed model can then be implemented in the network as a whole and therefore a crisp value of the LP will be evaluated for the whole WDS.

### 4.4.1 Study Area– Bangkok's Metropolitan Water Authority

To evaluate the practicality of this research, the model has been implemented for a small district metering area (DMA) of the Metropolitan Water Authority (MWA) of Bangkok (Thailand). The MWA is responsible to supply good quality water to its consumers (residences, businesses, and industries) in Bangkok and its surrounding provinces of Nonthaburi, and Samut Prakan (Figure 4.9). The water supply system consists of 15 service areas with 14 branch offices and one separate office in-charge of the water provision, consumer services, pipe and valve repairs, meter replacement, meter recording, bill collection and other related services (MWA 2005). The study area is located at the Bangkoknoi branch.


Figure 4.9: MWA service area

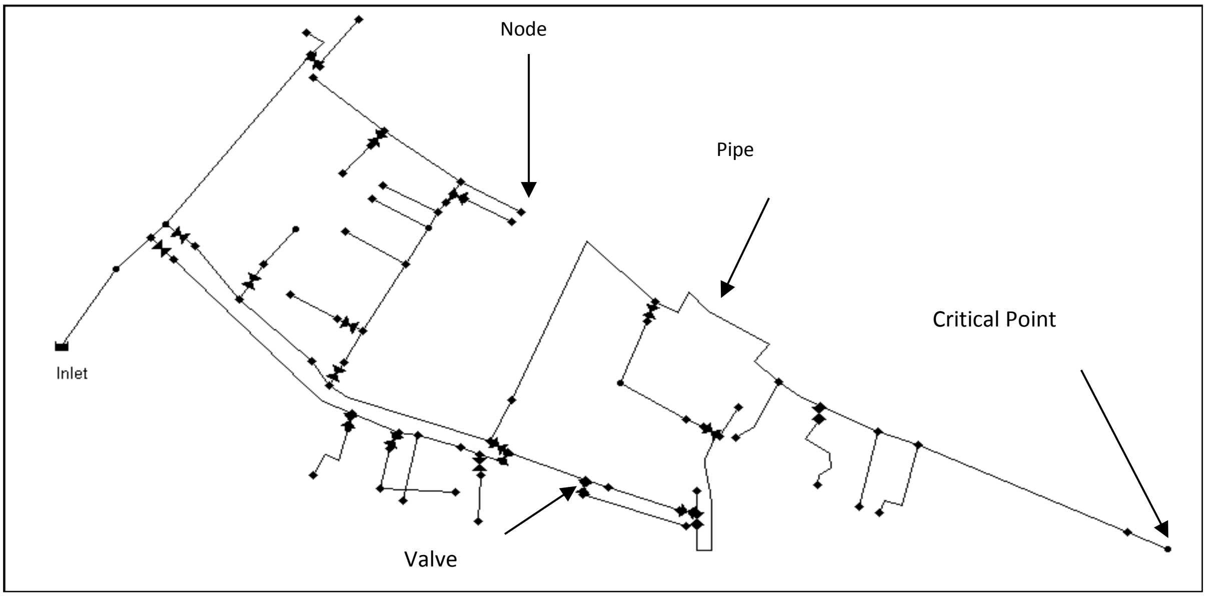



Figure 4.10: Network layout for DMA-00144

The Bangkoknoi office operates about 1,200 km of pipe network. All the pipes in the network are not of the same ages and characteristics. Most of the pipes in the Bangkoknoi branch network which is located at the oldest part of the MWA network have been in use for more than 25 years (Islam 2005). The whole service area of the Bangkoknoi branch is divided into six zones (zone 1 to zone 5 and zone 7). Under each zone, there are several DMAs. The present study is carried out for one of the DMAs of zone 1 named DMA-00144. Figure 4.10 shows the network layout for the DMA-00144.

The studied distribution network is comprised of an inlet (entry of water from the large network) and 60 pipes with a total length of 17.5 km connected by 77 junctions and 19 different types of valves. Additional basic information about the study area has been presented in Table 4.2. The rate of leakage in any WDS is highly influenced by the types of pipe material. About 49.8% of the pipe materials in the case study network are polyvinyl chloride (PVC), while 40.9% are asbestos cement (AC). The percentage of metal pipes, steel (ST), galvanized iron (GI) and cast iron (CI) are around 10% (Islam 2005). The next section provides more detailed information on the case study and its background.

### 4.4.2 Data Collection

A list of 24 factors has been identified which directly and/or indirectly influence the leakage potential. Most of the information related to these factors is also necessary to construct a hydraulic model of the network. To develop the hydraulic model, a set of necessary information was collected from MWA, Bangkoknoi office. This collected set of information has been used for the modelling of the LP. Babel et al. (2009) and Islam and Babel (2012) reported more details of the network hydraulic modelling and relevant information .

The average operating system pressure during the night time is very low compared to the operating system pressure at day time. A three day (1-2-3 September, 2004) average night time (00:00 am to 01:00am) minimum operating system pressure was as low as 4.47 m (6.39 psi), however, the average day time (12:00 to 13:00) maximum operating system pressure was 18.76 m (26.80 psi). The average operating system pressure for the period of 1-2-3 September, 2004 was 12.56 m (17.94 psi). There is a seasonal variation of the operating system pressure in the system to a considerable extent. For example, the average daily average operating pressure for the second half of February, 2004 (16-29 February, 2004) was 7 m (10 psi) (Islam 2005). This research evaluates the network based on an average operating system pressure (i.e., 12.56 m) during 1-2-3 September, 2004.

This study assumed a reference system pressure for the network as 25 m (35.71 psi), which is lower than the recommended value. Lower value was accepted here since most of the time the network operates relatively in low operating system pressure. The value of pressure exponent, the

*N1* has been estimated using pressure step test. From the pressure step test, the estimated value of *N1* for the study area is 1.16 (Islam 2005)[14].

Figure 4.11: Typical pipe trench in the study area

Table 4.2: Study area at a glance

| Actual Data | Value |
|---|---|
| Area coverage | 2.5 $km^2$. |
| Population served (estimated) | 3570 |
| No. of metered properties | 820 |
| Total Pipe length | 17.5 km |
| Average daily pressure (Sept' 04) | 12.56 m (17.94 psi) |
| Non-revenue water, May 2004 | 37.30% |
| Maximum diameter of the pipe | 300mm |
| Pressure Exponent | 1.16 |
| Major Pipe Materials | PVC, AC |

The study-area DMA is located in a residential area in the southern part of Bangkok where traffic flow and loading are not heavy. Consequently, a medium traffic loading and traffic flow has been considered. Cover depth, different types of workmanship of each pipe has been also estimated

[14] Details of N1 calculation is out of scope of this study. However, it could be obtained from author on request.

based on site working experience in the area. Figure 4.11 shows a typical pipe laying practice and cover depth in the study area.

Table 4.3: Data used for the modelling of LP for the study area

| Parameter Number | Parameter name | Symbol | Unit | Modelled Mean Value | Standard Deviation | Source |
|---|---|---|---|---|---|---|
| 1 | Traffic loading | LD | KN | 70 | 17.5 | A |
| 2 | Traffic flow | FL | Veh./hr | 3000 | 750 | A |
| 3 | Cover depth | CD | m | 0.6 | 0.15 | A |
| 4 | Soil type | ST | % finer | 30 | 7.5 | SR, A |
| 5 | Temperature fluctuation(ground) | TF | 0C | 1 | 0.25 | A |
| 6 | Groundwater table fluctuation | GF | m | 1 | 0.25 | A |
| 7 | Pipe materials | PM | None | 0.4 | 0.1 | I,A |
| 8 | Pipe diameter | PD | mm | 300 | 75 | I |
| 9 | Number of water meter | NM | No./km | 47 | 11.75 | I |
| 10 | Number of service Connection | NS | No./km | 47 | 11.75 | I |
| 11 | Number of joints | NJ | No./km | 10 | 2.5 | A |
| 12 | Residential demand | RD | None | 0.3 | 0.075 | A |
| 13 | Commercial demand | CoD | None | 0.6 | 0.15 | A |
| 14 | Industrial demand | InD | None | 0.6 | 0.15 | A |
| 15 | Pipe placement | PP | None | 0.3 | 0.075 | A |
| 16 | Bedding and backfills | BB | None | 0.3 | 0.075 | A |
| 17 | Compaction | C | None | 0.3 | 0.075 | A |
| 18 | Network instrument workmanship | NIW | None | 0.3 | 0.075 | A |
| 19 | Reference system pressure | RP | m | 25 | 6.25 | A |
| 20 | Pressure exponent | N1 | None | 1.16 | 0.29 | I |
| 21 | System pressure | SP | m | 12.56 | 3.14 | I |
| 22 | Head loss | HL | m/km | 0.4 | 0.1 | I |
| 23 | Pipe age | PA | Year | 25 | 6.25 | I |
| 24 | Network instrument age | IA | Year | 25 | 6.25 | I |

A= Assumed data based on site working knowledge; I= Islam, 2005; SR=Salokhe and Ramalingam, 2001.

Bangkok has predominantly clay soil (Salokhe and Ramalingam 2001). Around the year, the temperature and groundwater table fluctuation is not very high. The study area is located in a residential zone where industrial and commercial water demands are lower compared to residential water demand. Based on the above background, Table 4.2 provides information for the study area which has been collected from MWA. Table 4.3 shows values for all 24 factors that are used to model LP for the study area. These values are based on Table 4.2 and the site working experience with a project for MWA, Bangkoknoi office.

### 4.4.3 Results and Discussion

The DMA-00144 covers a very small area (2.5 km$^2$). Head loss from inlet point to most critical point (where pressure is minimal than any part of the network in all times) is less than 0.5 m (Islam 2005). Moreover, detailed information about each component of the network is not easily available. Therefore, the research assumed that the whole study DMA has similar characteristics (i.e., similar cover depth, traffic flow, traffic loading, temperature variation, reference pressure, pressure exponent, age, etc. for all pipes and network components) and average operating system pressure represents the pressure of the whole study DMA. Consequently, the model has been applied as a whole to the DMA and the estimated LP represents LP for the whole study DMA.

Using the proposed model, for current operating system pressure the estimated LP for DMA-00144 of Bangkoknoi office is 49%. Appendix A provides a step-by-step procedure for estimating LP. An LP 49% indicates that in the current situation, if no leakage reduction or control measures are taken then 49% of inflow would be lost due to leakage. It can be noted that the calculated LP and estimated leakage rate are not same. The calculated LP from a distribution network will not change based on short term leakage control and reduction activities.

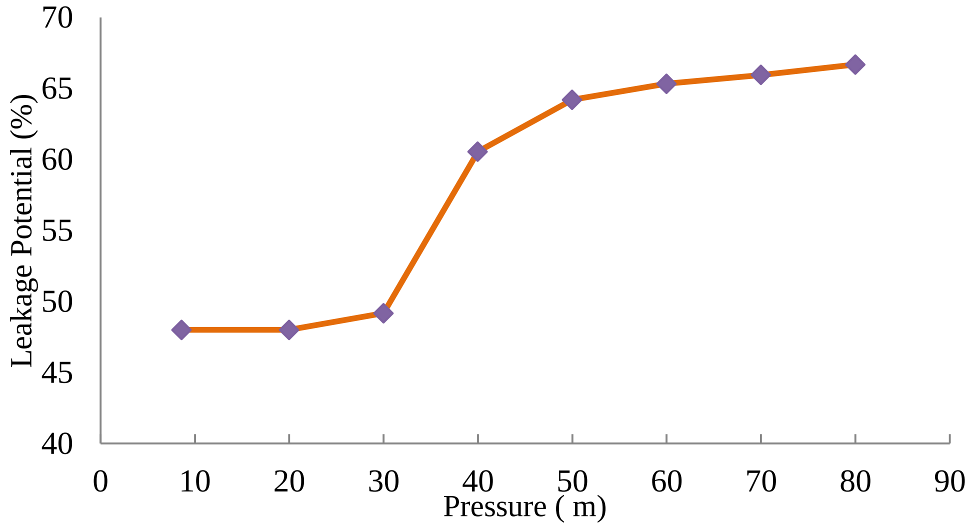



Figure 4.12: LP with varying pressure

However, leakage volume varies with the change of short term leakage reduction and control activities. It is expected that the estimated LP will be always higher than or equal to current leakage rate. Although 24 factors are identified contributing to LP, some of the factors have a major influence whereas others' influences are minor. It is identified (Figure 4.12 and Figure 4.13) that in a certain range, the operating system pressure and age of the network are the most important factors to contribute to LP. To observe the impact of pressure on LP, LP has been estimated for various system pressures while all other factors remain constant.

Figure 4.12 shows that, for the existing network condition, for operating system pressure less than 30 m (42.86 psi), the network LP is not very sensitive to pressure. However, when pressure exceeds 30 m (42.86 psi), the network LP is more sensitive to the operating system pressure. As stated earlier, the current average operating system pressure in the study DMA is 12.56 m (17.94 psi). This value is very low compared to pressure in any European or North American WDS. For example, the median of average operating system pressure in England and Wales is 42m (60 psi) (Farley and Trow 2003).

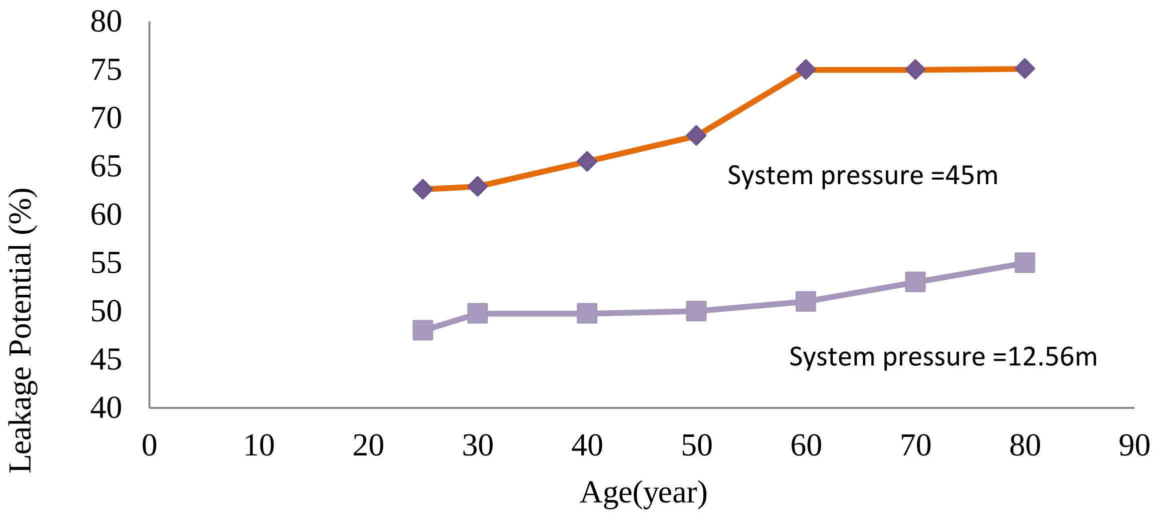



Figure 4.13: LP with age for two different operating system pressures

Figure 4.12 also shows that after 60 m (85.71 psi) of pressure the rate of change in LP is relatively small. This is mainly because the WDS will be nearly in failure state if the system approaches that level of pressure and age. Similar analysis has been carried out for various ages of network keeping all the other factors unchanged. Figure 4.13 reveals the results. Clearly, it appears that the impact of age to LP is very gradual for the current operating system pressure of 12.56 m (17.94 psi). However, if the operating system pressure increases to 45 m (64.29 psi), LP will increase more noticeably for same age combination (Figure 4.13). Additionally, Figure 4.13 reveals that for higher operating system pressure, LP is more sensitive in the age range of 30 - 60 years. This also indicates that the network will be virtually unusable after 60 years as the LP will be very high.

### 4.4.4 Sensitivity Analysis

Uncertainties are inherently present in different influencing factors. To evaluate the impacts of different uncertain parameters[15], the research has applied Monte Carlo (MC) simulation programmed in standard MATLAB coding environment, while the Spearman rank correlation coefficients have been used to compare the impacts of different influencing factors.

As stated earlier, this research has identified a list of 24 leakage influencing factors for which uncertainties has been modelled by assigning a probability distribution to each input factor/parameter. The research applied a normal distribution for all basic factors. The means and standard deviations of all parameters have been assumed based on estimated and/or observed value. Due to lack of data, standard deviations for each factor has been assumed as 25% of the mean as assumed for demand multipliers by Torres et al.( 2009).

The impacts of uncertainties of each factor/ parameter are related to the estimated values of parameters or factors, not general for all ranges of values of parameters. The estimated factors might be more or less sensitive in a certain range of their values. For example, LP is less sensitive to an operating system pressure when it is less than 30 m (42.86 psi). The sensitivity becomes more considerable when operating pressure is greater than 30 m (42.86 psi).

MC simulations generate multiple trial input values to estimate the value of random outputs. It also predicts the error in the analysis which is inversely proportional to the number of iterations. According to ProjectSmart (2010), total error in MC simulation can be estimated by:

$$\varepsilon = \frac{3\sigma}{\sqrt{N}} \qquad [4.20]$$

where, $\sigma$ is the standard deviation and $N$ is the number of iterations. This equation has been used to estimate the number of iterations for each MC simulation. Considering 1.5% error, the number of trials has been calculated for the all 24 variables. The estimated maximum number of trials is 1600. However, for this study, 2000 iterations were carried out. Four scenarios (Table 4.4) have been generated for the analysis.

[15] Modeled factors are termed as parameters. However, in some cases parameters and factors have been used interchangeably.

Table 4.4: Definition of scenarios analyzed

| Scenarios | Variables | Constant Parameters[16] | Special Treatment |
|---|---|---|---|
| Scenario I | All except constant parameters | RP,N1,SP, HL,PA,IA | None |
| Scenario II | All | None | None |
| Scenario III | All | None | Mean operating system pressure = 45 m |
| Scenario IV | All | None | Mean operating system pressure = 45m<br>Mean network age =35 years |

Furthermore, in the sensitivity analysis, to compare parameter-wise influence to LP, Spearman rank correlation coefficients were estimated. If $u_i$ is trial values of any input parameter and $v_i$ is the corresponding LP values for those trial values, then the Spearman rank correlation coefficient can be calculated by using Equation 4.21 (Walpole et al. 2007):

$$r_s = 1 - \frac{6}{n(n^2-1)} \sum_{i=1}^{n} d_i^2 \qquad [4.21]$$

where $i$ =1, 2, 3 ... $n$; $n$ is the number of pairs of data (number of iterations) and $d$ is the difference between the ranks of the $i^{th}$ value ($u_i$) of input parameter and the corresponding LP value ($v_i$).

#### 4.4.4.1 Scenario I

As stated earlier, the most influencing factors for LP are pressure (e.g., reference system pressure, pressure exponents, head loss and operating system pressure) and network age (e.g., age of the pipe, age of the network instruments). To see the impacts of other factors, the sensitivity analysis using MC simulation has been carried out. Figure 4.14 presents (a) probability distribution function (PDF) and cumulative distribution function (CDF); and (b) Spearman rank correlation coefficients. Figure 4.14 (a) shows that LP is not very sensitive and most of the iterations calculated LP around 48%. Figure 4.14 (b) shows that cover depth and traffic loading are the most influencing factors. It is industry practice to respect a minimum cover depth of 1.2 m for a buried pipe. If this cover depth decreases while traffic loading and traffic flow increase, the risk of pipe failure will increase significantly. Therefore, traffic loading is positively correlated whereas cover depth is negatively correlated. For the study network, the assumed mean cover depth and standard deviation is 0.6 m and 0.15 m, respectively. The small cover depth makes the network very vulnerable against traffic impact.

[16] See Table 3 for full name of abbreviate parameters

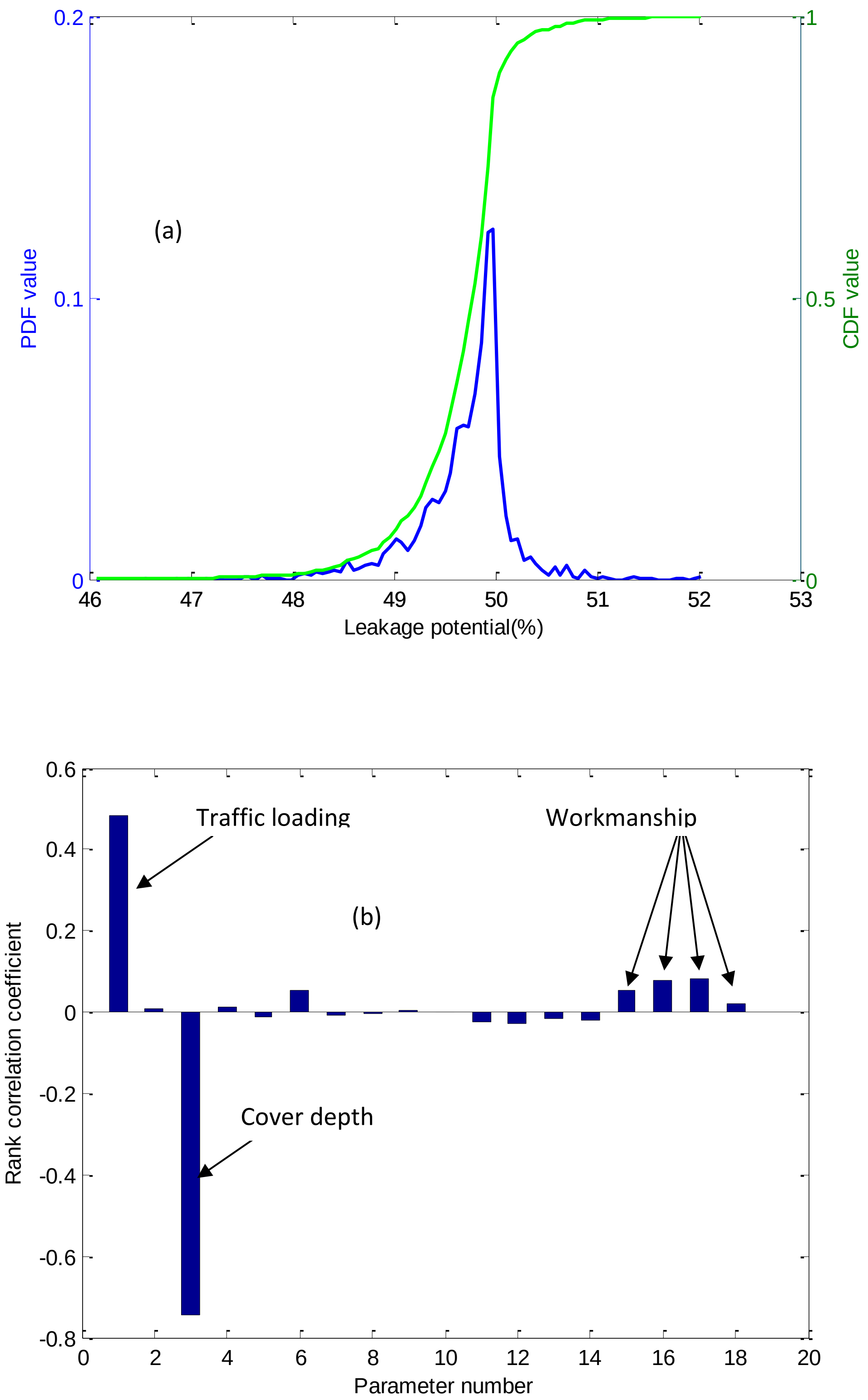



Figure 4.14: MC simulation results for Scenario I (a) PDF and CDF (b) Spearman rank correlation coefficients

However, if the covered depth would have been more than 1.2 m then the cover depth and loading would not be that sensitive. After the traffic factors, the workmanship parameters are the next sensitive factors. This research studied four workmanships factors (e.g., pipe placement, bedding backfilling, compaction and workmanship for network instruments).

#### 4.4.4.2 Scenario II

Similar to Scenario I, for current operating condition a MC simulation has been carried out considering all factors as variable. Both PDF and CDF, and the Spearman rank correlation coefficients are presented in Figure 4.15. Figure 4.15 (a) shows that the shapes of PDF and CDF have not changed significantly as compared to Scenario I shown in Figure 4.14 (a). However, an additional peak is observed in PDF curve indicating less sensitivity of LP against the low operating system pressure.

However, the small gap (i.e., distance) between the two peaks on Figure 4.15 (a) indicates less sensitivity of LP for this scenario. Nevertheless, the network might behave quite differently if the operating system pressure increased to a range 30 – 60 meter shown in Figure 4.12. These analyses have been conducted in Scenarios III and IV explained in the next two sections. Note that as Figure 4.12 indicates LP is not very sensitive to operating system pressure below 30 m. First small peak in Figure 4.15 (a) represents that less sensitive value. On the other hand, Figure 4.13 suggests that at the age below 60 years for low pressure (e.g.,12.56 m or 17.94 psi) and below 30 years for high pressure (e.g., 45 m or 64.29 psi), LP is not very sensitive to the age of the network (i.e., the age of the pipes and age of the network appurtenances).

The estimated leakage potentials for these two cases are around 50% and 62%, respectively. The second peak of Figure 4.15 (a) represents less sensitive value. The Spearman rank correlation coefficients given on Figure 4.15 (b) reveal that the age of the pipe becomes more sensitive than cover depth. This study assumed the mean and standard deviation of the age of the network are 25 years and 6.25 years, respectively. In addition to the impact of the network age, the cover depth and traffic loading are the most critical influential factors.

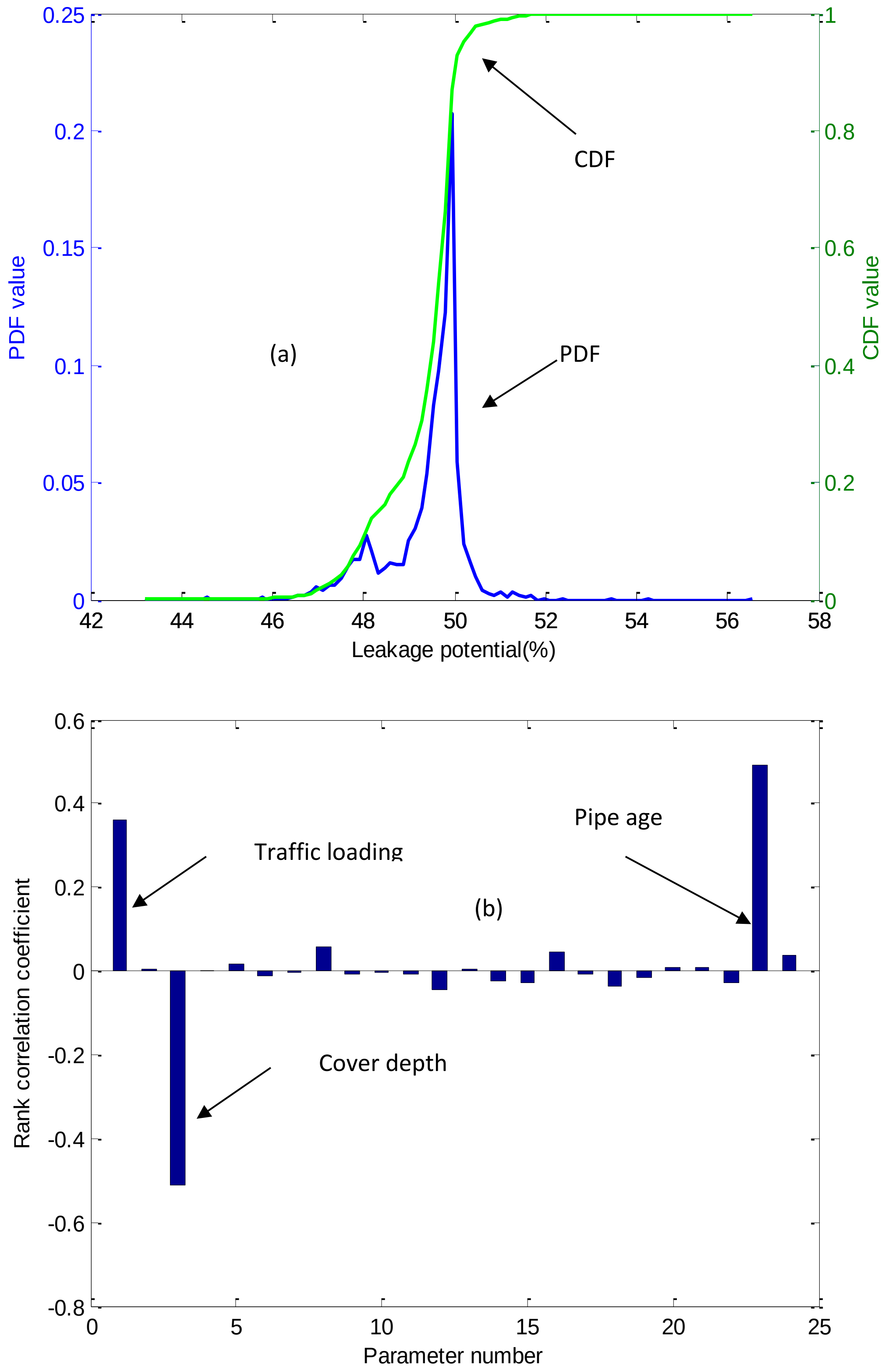



Figure 4.15: MC simulation results for Scenario II (a) PDF and CDF (b) Spearman rank correlation coefficients

#### 4.4.4.3 Scenario III

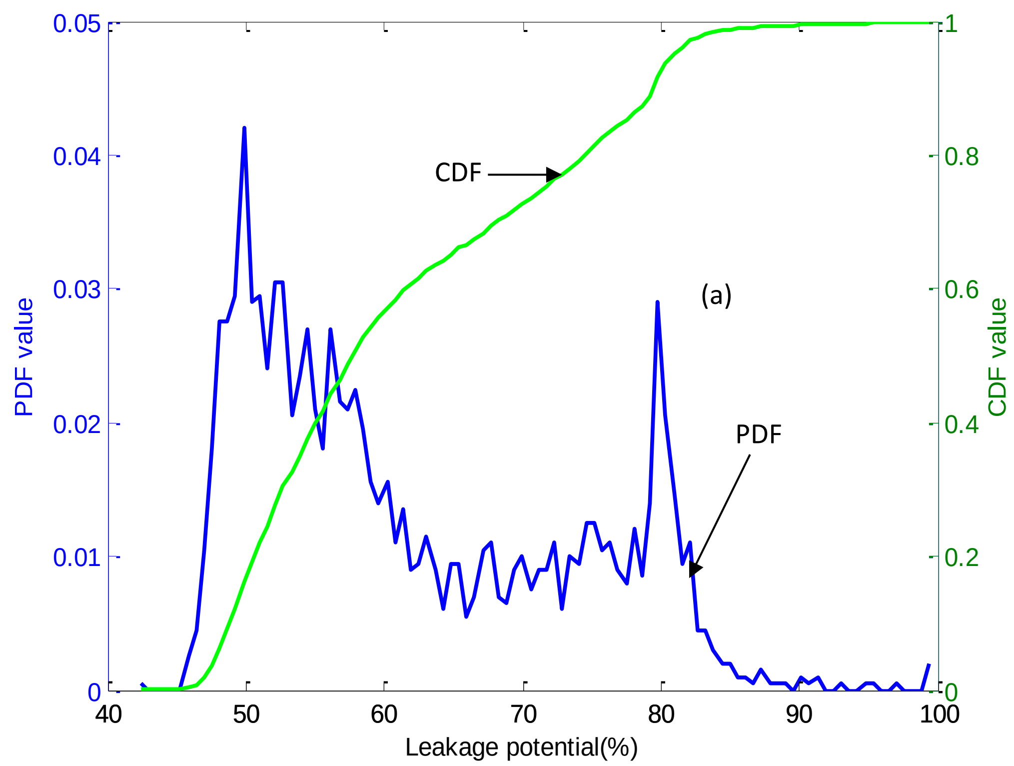
In this scenario, MC simulation has been carried out considering all parameters as variable for the current operating condition. However, operating system pressure has been changed to 45 m (64.29 psi). This pressure has been selected from the sensitive region of Figure 4.12. Figure 4.16 shows the results for (a) PDF and CDF and (b) Spearman rank correlation coefficients. Though Figure 4.15 (Scenario II) and Figure 4.16 (Scenario III) show nearly similar shape of the PDF, Figure 4.16 represents a wide range of LP. This wide range indicates that with increase of pressure, influences of all other factors change significantly. The point of inflection in the CDF curve represents the second peak of PDF. Therefore, the point of inflection in the CDF curve indicates less sensitivity of LP for parameters at that point.

From Figure 4.16 (b), it is evident that the system pressure and pressure related factors become the main drivers. The most influencing factors are system pressure, pressure exponent, reference system pressure, age of the network and cover depth. It is important to note that reference system pressure is negatively correlated with LP which means with the decrease of reference system pressure, LP will increase for the same system operating pressure.

#### 4.4.4.4 Scenario IV

This scenario is identical to Scenario III except that the age of the network has been increased to 35 years. Similar to previous three scenarios, Figure 4.17 shows (a) PDF and CDF and (b) Spearman rank correlation coefficients. The difference in two peaks of Figure 4.15 (Scenario II) and Figure 4.16 (Scenario III) become less noticeable. Therefore, the point of inflection in the CDF is less visible. It is also observed that due to increase of age, the value of PDF has increased towards the highest range of LP.

This indicates that if the network age is around 35 years and operating system pressure is 45m, the network will be virtually unable to deliver water to the consumers. Like scenario III, Figure 4.17 (b) reveals that operating system pressure and pressure related factors are the most influencing factors followed by the age of the pipe.



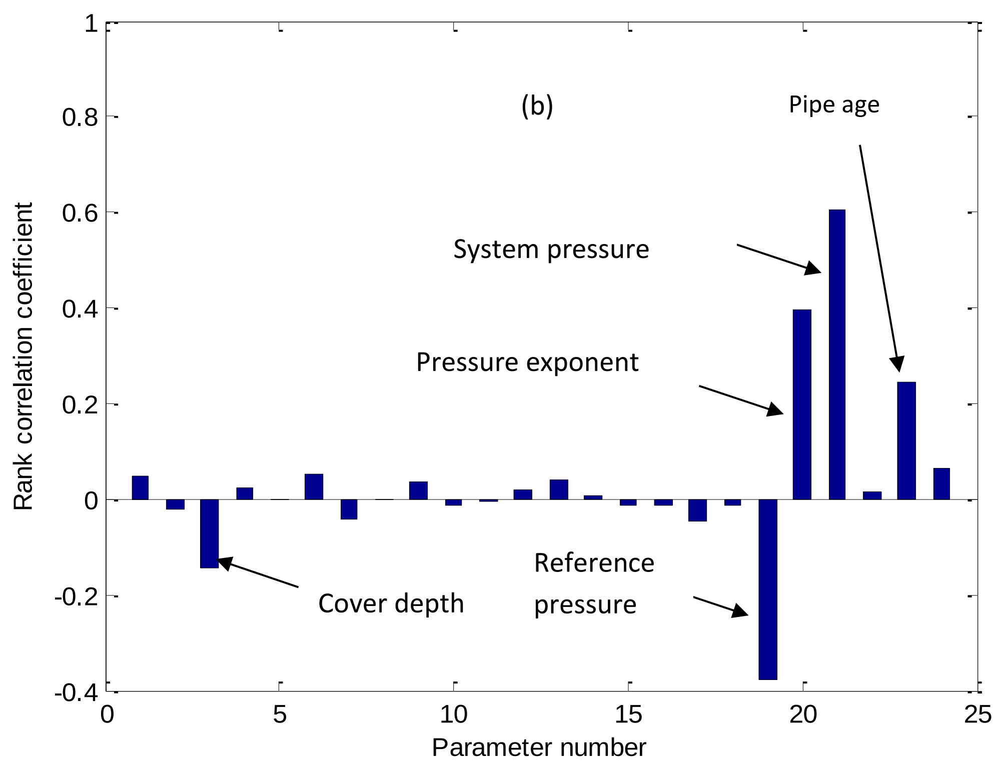




Figure 4.16: MC simulation results for Scenario III (a) PDF and CDF (b) Spearman rank correlation coefficients

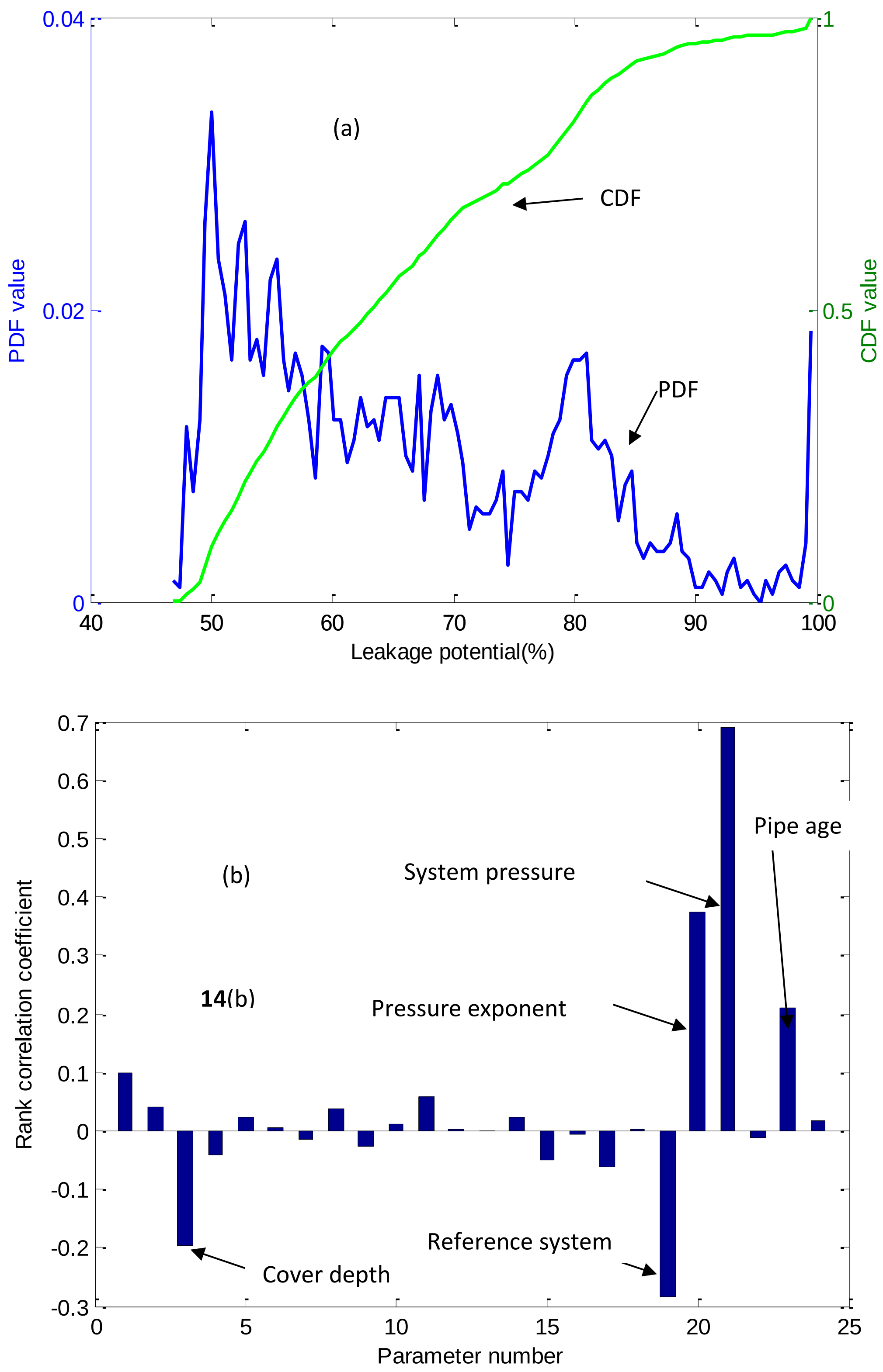



Figure 4.17: MC simulation results for Scenario IV (a) PDF and CDF (b) Spearman rank correlation coefficients

## 4.5 Model Summary

This part of the research developed a FRB model to estimate LP for WDS identifying various key leakage influencing factors. A normalization method has been adopted which will simplify the interpretation of the FRB modelling results to the non-technical people. Additionally, a new adjusted FRB methodology has been proposed to adjust the impact of such factors which can also influence other contributory factors.

Detailed sensitivity analysis revealed that the operating system pressure and pressure related factors such as reference system pressure and pressure exponent are the most influencing factors. The results also confirmed that after pressure related factors the pipe age are the most important factor. However, the sensitivity of these factors varied according to the range of operating system pressure and network age. It is also identified that cover depth of the pipe is very influential in a certain range. However, cover depth is less pressure dependent. The next influencing factors are different kinds of workmanship of the network and network appurtenances. It is noted that among twenty four factors around half (e.g., pressure related factors, age, workmanships, cover depth) of them are the most influential on the LP and the remaining half of the factors (e.g., groundwater table fluctuation, head loss, soil type) have minimal influences.

Though this model has been applied to a network of low pressure, the model can be used for any network by modifying appropriate factors/parameters. Indeed, the model should be updated based on any specific condition of any particular network, especially ranges of different influencing factors. Moreover, the developed methodology can be extended for other cases for similar problem. For the case study, some of the data have been estimated based on the information collected from state-of-the practice, manuals and the experience in the study area. However, by collecting these data, estimated LP would be more accurate. Like almost all risk-based modelling approaches, this study also suffers from lack of validation data. In spite of the limitation, the proposed methodology is capable of helping water utility managers to prioritize their leakage control and rehabilitation policy through better understanding of their network.

In future studies, the developed model could be linked with US EPA developed EPANET model as an add-on. That will give the capability to EPANET to calculate LP for pipes and to map the spatial distribution of LP within WDS.

# CHAPTER 5 LEAKAGE DETECTION AND LOCATION MODEL

An version of this chapter has been published in Urban Water Journal [8(6), 351–365] with the title "*Leakage Detection and Location in Water Distribution System Using a Fuzzy-Based Methodology*" (Islam et al. 2011b).

## 5.1 Background

As stated earlier, leakage from a WDS is a universal problem. There is no single reason for the occurrence of leakage in any WDS. There are numerous physical, environmental, and hydraulic factors that pose threats to make WDSs vulnerable to leakage. Whatever the reasons might be, if the leakage is identified, and controlled in a minimal time after its occurrence, a significant volume of treated water can be saved.

From the time of occurrence of WDS's leakage, to its return to a normal operating condition, the time can be divided into three stages (ALR): (a) leakage awareness time, (b) leakage location time, and (c) leakage repair time. Awareness time is the time necessary for a utility organization to be aware of the existence of leakage in a system. The location time is the time necessary for a utility to locate the leakage after being made aware of its existence, and the repair time is the actual time necessary for repairing the leakage (Farley and Trow 2003). After an occurrence of leakage, if these three times (ALR) are minimal, then the water lost through leakage from the system will be minimal. However, the ALR time necessary for a system depends on leakage detection processes, best management practices, technologies, the number and the skill of the staff involved, and overall, most importantly, an active leakage control (ALC) policy of the utility. For example, a WDS with regular sounding[17] once per year, the average duration for awareness and locating for a leakage in a service pipe or main would be 183 days (Lambert 1994). On the other hand, if a utility checks for leakage on a daily basis, the awareness and the

[17] A systematic survey technique for listening for leak noises on hydrants, valves, stop taps or at the ground surface above the line of the pipe line. Various types of equipment are available; however, the sounding stick is a basic one, which can be used as a simple acoustic instrument or an electrically amplified instrument (Farley and Trow 2003).

leakage location time will be significantly lower. Table 5.1 compares average running times for an unreported burst under different WDS monitoring conditions, where an unreported burst refers to the burst that runs until identified by an active leakage control action (Lambert 1994). It is obvious that a fast detection can save awareness time significantly, which eventually save a large volume of water leaking from a WDS.

Over the last hundred years, water utilities have been using different techniques, including manual sounding, acoustic loggers, ground-penetrating radars, helical vane meters, deacon meters, leak noise correlators, step testing, combined acoustic loggers and correlators, electronic step testers, digital correlators, advanced ground microphones, and so forth to detect leakage in their systems (Pilcher 2003). In recent times, the real time monitoring of WDS using different sensors has been used to detect anomalies in water distribution systems. Water utilities have been adapting real time monitoring techniques, coupled with burst and background estimate (BABE)–a component-based leakage volume estimation (Lambert 1994) technique to estimate the leakage in WDS. But, generally, the real time monitoring is not enough to detect the leakage. Information needs to be extracted by analyzing the monitored data to detect leakage. An efficient detection and diagnosis algorithm is prerequisite to identify leakage in a WDS. There have been many studies conducted to increase the efficiency and the confidence of the detection and diagnosis algorithms. A summary of some of the important studies relevant to this research has been reported in literature review chapter. Each of the reported algorithms and formulations has some noted advantages but also suffers constraints. There are many other related studies (e.g., Covas et al. 2005; Webb et al. 2009) that highlight the importance of continuing research for leakage detection and diagnosis.

Table 5.1: Importance of time and technology in leakage (Modified from Lambert 1994)

<table>
<tr><th rowspan="2">WDS Type</th><th rowspan="2">Leakage control policy</th><th colspan="3">Average running duration (days)</th></tr>
<tr><th>Awareness</th><th>Location</th><th>Repair</th></tr>
<tr><td rowspan="3">Non-metered WDS</td><td>Sounding once in two years</td><td>365</td><td rowspan="6">1 to 2 days*</td><td rowspan="6">Between 4 to 10 days*</td></tr>
<tr><td>Sounding once in one year</td><td>183</td></tr>
<tr><td>Sounding twice in one year</td><td>93</td></tr>
<tr><td>Metered WDS</td><td>Monthly meter reading</td><td>15</td></tr>
<tr><td>Metered WDS with data logger</td><td>Weekly data download</td><td>3 to 4</td></tr>
<tr><td>No-metered WDS with telemetry</td><td>Continuous</td><td><1</td></tr>
<tr><td colspan="5">*Highly depended on employed technology and also number, capabilities and efficiency of the leak location and repair staff.</td></tr>
</table>

Generally, the literature on leakage detection and diagnosis acknowledge high levels of uncertainties. However, most of them did not incorporate the uncertainties related to the different WDS parameters in their algorithms, and even when incorporated, it was poorly addressed. Therefore, the reported algorithms may either produce many costs-incurring false positive alarms or fail to detect real leakage events by generating false negative alarms.

A WDS is a distributed system consisting of a set of links and nodes. The physical junctions of the pipes, points of any changes in linear pipes, reservoirs, and tanks are generally known as nodes, whereas all the pipes, valves, and pumps are considered links. Due to the continuous changes in friction coefficients, nodal demands, and reservoir water levels, it is very difficult to predict those parameters. Because of the semi-quantitative nature of the independent parameters, the simulated WDS dependent parameters (i.e., pressure at nodes and flow in pipes) are subjected to uncertainties.

Using fuzzy-based algorithms, Revelli and Ridolfi (2002) proposed an optimization-based methodology in order to address this issue by calculating the extreme values (i.e., maximum and minimum) of the WDS dependent parameters. Gupta and Bhave (2007) developed a methodology to incorporate the parameter uncertainties using a fuzzy-based approach. To obtain the same solution for the WDS used by Revelli and Ridolfi (2002), the algorithm developed by Gupta and Bhave (2007) , however, requires less computational efforts. Using normal values of the independent parameters (e.g., roughness coefficients, nodal demands, reservoir water levels, and so forth), the normal values of the dependent parameters, such as pressure, quality, and age, of water for all nodes, and flow, velocity, and quality of water within all pipes, were simulated. However, the maximum and the minimum values of independent parameters did not produce the maximum and the minimum values of the dependent parameters, respectively. This study showed that some combinations of maximum and minimum values of the independent parameters may produce extreme values of the dependent parameters (Gupta and Bhave 2007).

Fuzzy sets are used to deal with vague and imprecise information (Zadeh 1965). Instead of providing any information with crisp value, fuzzy sets model the information with a degree of membership where the most likely value has a full degree of membership, and the least likely values have the zero membership. Fuzzy set theory is widely applied to solve real-life problems that are subjective, vague, and imprecise in nature (Smithson and Verkuilen 2006; Yang and Xu 2002). Since its conceptualization, fuzzy set theory has been used in various engineering applications, including civil and water engineering. It is successfully implemented for structural damage analysis, vibration control of flexible structures, cement rotary kiln control, and concrete analysis and design (Gad and Farooq 2001). Sadiq et al. (2007) implemented fuzzy sets for predicting water quality failures in WDS. There are numerous other examples for the application of fuzzy sets in water distribution modelling.

## 5.2 Leakage Detection and Location Model Development Methodology

This section of this research proposes a novel methodology to detect the presence of leakage, and highlights the most likely leakage location in WDS. To better address the uncertainties in the proposed leakage detection and diagnosis methodology, the uncertainties of different independent parameters are described using fuzzy sets. Fuzzy set theory has been used for modelling complex systems, and handles uncertain and imprecise information effectively (Ross 2004). In this study, the algorithm developed by Gupta and Bhave (2007) has been adopted to simulate the maximum and the minimum values of the dependent parameters for an extended period of simulation. Monitored pressure in different nodes and flow in different pipes are used to estimate the degrees of memberships of leakage and its severity in terms of index[18] of leakage propensities (ILPs). The ILPs help to identify the most likely leakage location in a WDS.

The proposed methodology requires the identification and fuzzification of different independent parameters such as roughness coefficients, nodal demands, and water reservoir levels, as well as three sets of WDS solutions. As reported in previous studies (Gupta and Bhave 2007; Revelli and Ridolfi 2002), it is assumed that the independent parameters are triangular fuzzy numbers. Three sets of WDS solutions include one set for a normal WDS condition to represent the most likely values, and two sets for the maximum and the minimum values of the dependent parameters (e.g., pressure in all nodes and flow in all pipes). The solution for a normal condition of a calibrated model estimates the values of dependent parameters (for all nodes and links), whereas the other two sets estimate the two extreme sets (i.e., maximum and minimum) of the possible values of dependent parameters (for all nodes and links). Details of the adopted methodology have been provided in Section 5.2.2. It is noted that the accuracy of the leakage detection depends on the well-calibrated model. However, in practice, the standard of hydraulic model calibration is not often pleasing. In such a situation, detection and location of a small leakage will be error-prone.

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[18] It is a ratio of deviation of the monitored flow from the most likely value to deviation of the extreme value from the most likely value. Details have been discussed in Section 5.2.4.

The EPANET (Rossman 2000) simulation engine and its source codes have been used for WDS simulation. Using the most likely values and the two extreme sets of independent parameters, the fuzzy numbers for the independent parameters are defined. Thereafter, using the simulation engine, the most likely and the two extreme sets of dependent parameters, and subsequently, the fuzzy numbers for the dependent parameters are defined.

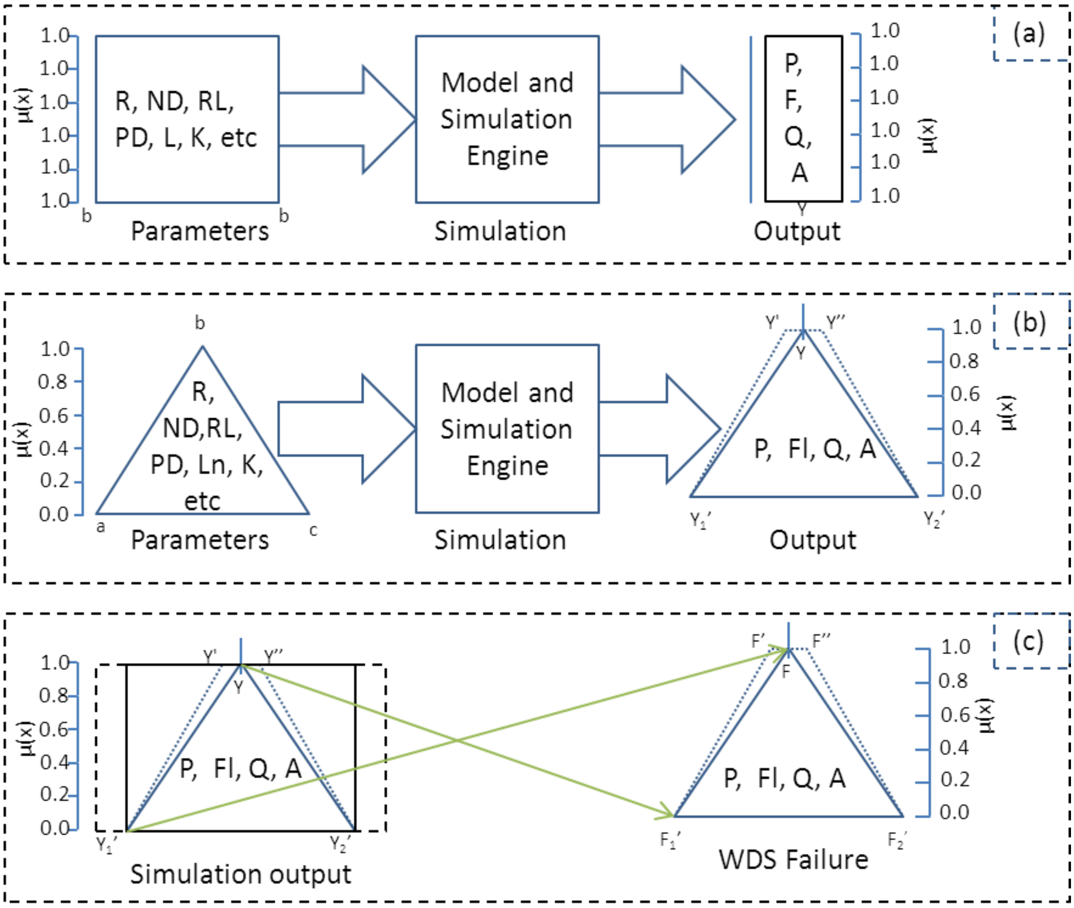



Figure 5.1: Conceptual framework of the proposed methodology

R=Roughness coefficients; ND=Nodal demands; RL=Reservoir water levels; PD=Pipe diameters; $L_n$=Lengths of the pipes; K=Head loss coefficients; P= Pressure; FL= Flow; Q= Quality; A= Water age; a= Lower level values of independent parameters; b= The most likely values of independent parameters; c= Upper level values of independent parameters; $Y_1'$= Lower level values of dependent parameters; $Y_2'$= Upper level values of dependent parameters; Y= The most likely values of dependent parameters; $F_1'$= Lower level values of the failure fuzzy number; $F_2'$= Upper level values of failure fuzzy number; F= The most likely values of failure fuzzy number; In case of certain percentage of deviation of the most likely values (shown in equation 4 as $p_1$) of dependent parameters or in case of ZFN (instead of TFN) is used for independent parameters, the most likely value Y could extend from two sides of the most likely values. In Figure 5.1 (b), Y' and Y'' represents the range of the acceptable deviation. Similar deviation is presented in Figure 5.1 (c) to represents WDS failure by F' and F''.

Data obtained from sensors have been compared with the developed fuzzy numbers for selected dependent parameters. It assumed that sensor data are reasonably correct and uncertainties in the sensor data have not been considered in this study. From the comparison, the degrees of leakage memberships and the indices of leakage propensity (ILPs) have been estimated for pipes and nodes. If a sensor data is same as the most likely value then the degree of leakage membership is zero, and if the sensor data is the same as the lowest value, then the degree of leakage membership is one. However, if the sensor data is higher than the most likely value it will not represent the leakage; it will indicate another form of anomaly such as blockage. The latter is not addressed in this study. Figure 5.1 provides the conceptual framework for the proposed methodology. Details of the algorithm are discussed in Sections 5.2.3 and 5.2.4. Different stages of the proposed methodology and the EPANET toolkits' functions have been implemented using MATLAB 7.10 (MathWorks 2010).

In Figure 5.1 (a), all the independent and the calculated dependent parameters are deterministic. Therefore, they have a full degree of membership of their values. However, in Figure 5.1 (b), all the independent and the dependent parameters are fuzzy and they have different degrees of membership of their values. In Figure 5.1 (c), the simulated most likely dependent parameters indicate no failure whereas any deviation from the most likely value indicates the presence of anomalies. The deviation up to their two extreme values indicates the full membership of their failure.

### 5.2.1 Identification and Fuzzification of Independent Parameters

Water distribution systems are complex infrastructures. Modelling of such an infrastructure involves many parameters, such as diameters, lengths and roughness coefficients of pipes, nodal demands, water levels in reservoirs and head-discharge characteristics of pumps, and performance characteristics of different valves and minor elements (Gupta and Bhave 2007). Among those parameters some are very precise, such as pipe lengths, some are imprecise such as roughness coefficients, and some are between, such as nodal demand, for which a statistical distribution can be generated if enough information is available (Revelli and Ridolfi 2002).

On the other hand, some of those imprecise parameters may a have significant impact on WDS, whereas some may have a low impact. Therefore, the parameters which are relatively imprecise, and have significant impact on the WDS simulation results have been selected for fuzzification. However, inclusion of all WDS independent parameters for fuzzification will not reduce the reliability of the results, but, will reduce the computational efficiency. Roughness coefficients, nodal demands, and reservoir water levels are considered the most common parameters which are imprecise and may have a significant impact on results (Gupta and Bhave 2007; Revelli and Ridolfi 2002).

After the selection of independent parameters, the most likely and the extreme values of the selected parameters are defined. The values of independent parameters of a calibrated model can be used as the best estimate for the normal values, whereas the extreme values can be estimated based on reported literature values, industry practice experience, and other supporting data or certain percentage of the normal values, defined based on experts' judgement. In Figure 5.1, the normal values of the independent parameters are represented by *b* whereas *a* and *c* represent the minimum and the maximum values, respectively (which can also be seen in Figure 5.2). Based on the minimum, the most likely and the maximum values of all the selected independent parameters, fuzzification has been carried out. To fuzzify the data, generally triangular fuzzy numbers (TFN) or trapezoidal fuzzy numbers (ZFN) are used (Lee 1996). All the selected parameters (e.g., roughness coefficients, nodal demands, reservoir water levels, head loss coefficients, and so forth) have been fuzzified (Figure 3.4). As described in Chapter 3, Equations 3.2 and 3.3 (Chapter 3) have been used to model the TFN and ZFN. For a TFN, *a* is the minimum value, *b* is the most likely value and *c* is the maximum value of an independent parameters. For a ZFN, *a* is the minimum value, *d* is the maximum value and *b* and *c* are the two values which represent the interval of the most likely value. It is assumed that the fuzzified values of independent parameters are in an *Nx*3 matrix [*a b c*], where *N* is number of an independent parameter.

Although the fuzzy independent parameters are strictly triangular or trapezoidal with linear sides (e.g., *ab'* and *b'c* for TFN and *ab'* and *c'd* for ZFN), the corresponding fuzzy numbers for dependent parameters will be also triangular or trapezoidal but with curvilinear sides (e.g., *ab'* and *b'c* for TFN and *ab'* and *c'd* for ZFN) (See Figure 3.4), because of the nonlinearity of the system (Revelli and Ridolfi 2002). However, the difference between the linear and the curvilinear sides is small (Gupta and Bhave 2007). Therefore, the fuzzy numbers for dependent parameters have been considered triangular or trapezoidal with linear sides.

### 5.2.2 Estimation of Extreme Values of Dependent Parameters

Following the steps described in section 3.2.2 in Chapter 3 , the extreme values of hydraulic dependents parameters are estimated. Based on the steps described in section 3.2.2 in Chapter 3, the fuzzy values of the dependent parameters for 24 hours can be estimated. Figure 5.2 shows the flowchart showing the different steps of the proposed algorithm.

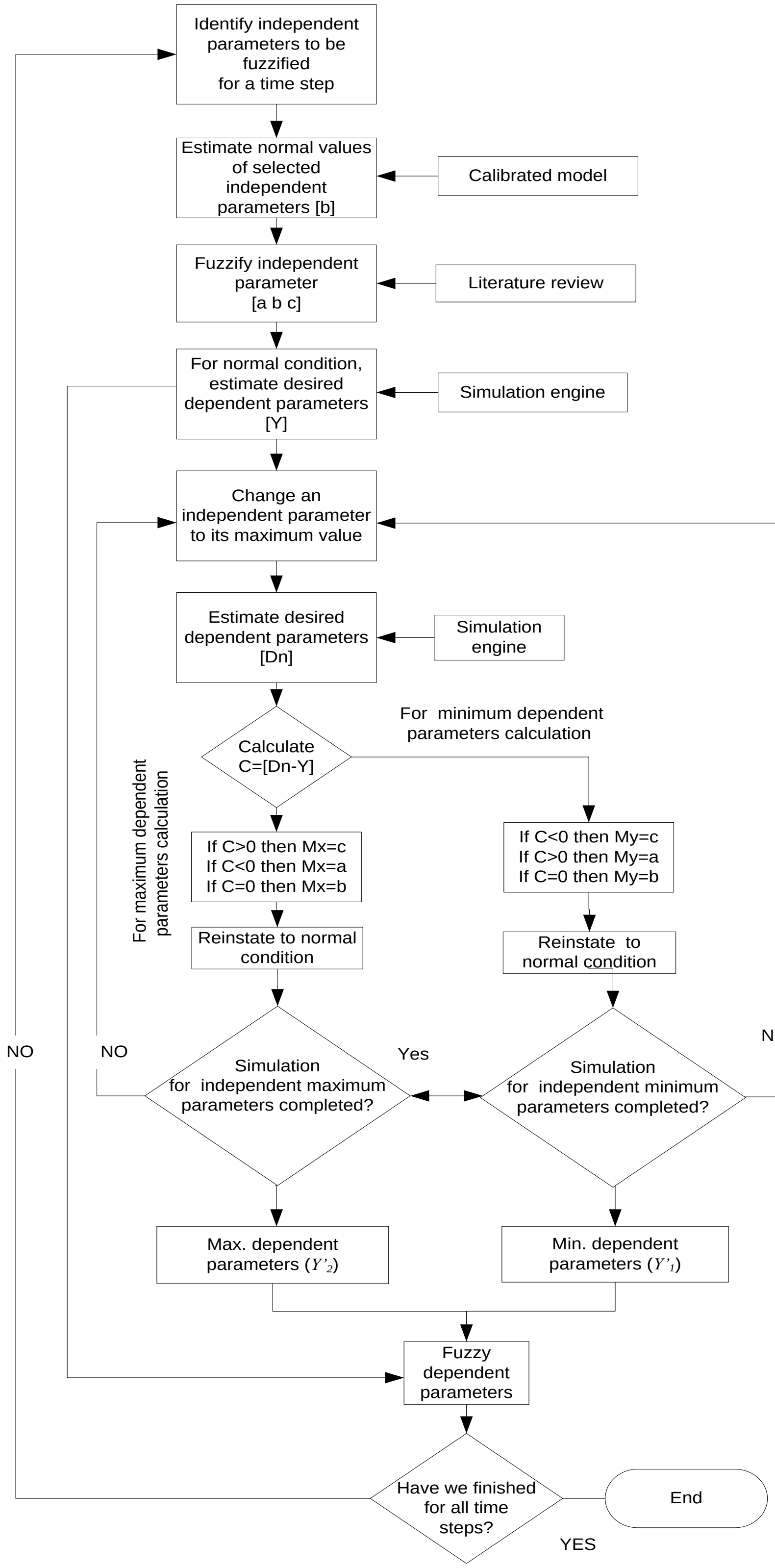



Figure 5.2: Flowchart for proposed methodology

### 5.2.3 Leakage Detection

This part of the algorithm has been developed based on the simulation results of an undamaged WDS. Under the assumption that *M* is a calibrated hydraulic model with an array of independent parameters, $X = \begin{bmatrix} X_{11} & \cdots & X_{1i} \\ \vdots & \ddots & \vdots \\ X_{j1} & \cdots & X_{ji} \end{bmatrix}$

where *i* represents different kind of the independent parameters such as the roughness coefficients, nodal demands, reservoir water levels, pipe diameters, pipe lengths, head loss coefficients, and so forth and *j* is the number of each *i*. For example, if *i* is the roughness coefficients then *j* is the number of pipes, and if *i* is the nodal demands, then *j* is the number of nodes. The simulation of a calibrated hydraulic model *M (b)* estimates an array of dependent parameters, $Y = \begin{bmatrix} Y_{11} & \cdots & Y_{1r} \\ \vdots & \ddots & \vdots \\ Y_{j1} & \cdots & Y_{jr} \end{bmatrix}$

where *r* is the number of dependent parameters such as pressure, flow, quality and *j* is the number of each *r*. Using the algorithm presented in Section 5.2.2, the WDS has been solved for the two extreme solutions. It is assumed that the extreme solutions of the WDS is $(Y'_{12})$, where $Y'_{12}$ represents both the minimum $(Y'_1)$ and the maximum $(Y'_2)$ solutions of all the dependent parameters. The monitored/ sensor data will be evaluated with respect to the fuzzy numbers defined from these three sets of solutions (Y, $Y'_1$ *and* $Y'_2$). Assume $\hat{Y}$ is an array of monitored / sensor data for a particular time, expressed as $\hat{Y} = \begin{bmatrix} \hat{Y}_{11} & \cdots & \hat{Y}_{1m} \\ \vdots & \ddots & \vdots \\ \hat{Y}_{k1} & \cdots & \hat{Y}_{km} \end{bmatrix}$

where *m* refers to different monitored parameters such as flow, pressure, quality and *k* is the number of each *m*. If all the dependent parameters are monitored then *m* and *r* will be the same number and if the monitored data are available for all nodes and pipes, then *k* and *j* will have the same number. In case of leakage detection, flow and pressure are considered as dependent parameters; therefore, $m = 2$ and $k$ = number of the monitoring locations at a particular time. After the selection of key parameters, the system will calculate the departures of the monitored values from the accepted $((Y_{ij})*p_1)$ values (Equation 5.1).

$$D_{km}(X) = (Y_{km})*(\pm p_1) - (\hat{Y}_{km}) \quad [5.1]$$

where, $p_1$ is the deviation factor. If no deviation of the calibrated values from the normal values is expected, then $p_1$ is considered as 1, provided that the defined independent fuzzy numbers are triangular. However, if a deviation of the calibrated values from the normal values is acceptable then $p_1$ could have a different value (based on the acceptable deviation). A situation is assumed where the calibrated model can estimate correct pressure and flow, and represents the most likely value. In Figure 5.3, the *Y* represents the most likely value and acceptable value of pressure and flow.

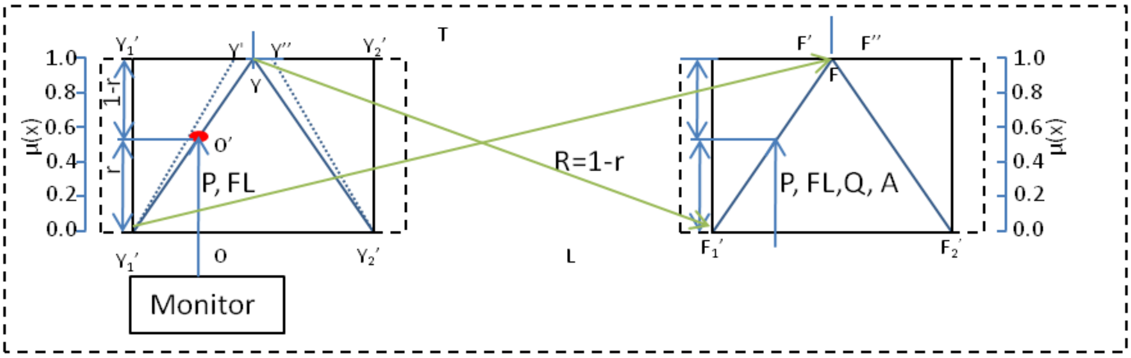



Figure 5.3: Leakage detection algorithm

If the monitored sensor pressure is in the range of acceptable values then no failure (either leakage or blockage) is considered. If the monitored pressure is less than the most likely value then the system anomaly is due to a leakage or an unusual demand in the system. However, if the monitored pressure is higher than the most likely value, then the anomaly is due to a blockage. If there is an unusual demand, it will not continue for long time, however, in case of leakage, it will continue until it is controlled. If the demand variation is due to another reason (e.g., repair or rezoning), the model can also detect that variation, however, the decision makers need to decide how to treat the detected variation. For a weekend demand variation, it is necessary to use a model calibrated for the weekend.

In general, the monitored values will have certain extent of deviations due to various uncertainties. These deviations can go up to the estimated two extreme values. If a monitored value of a sensor goes to any of the two extreme values or beyond then the anomaly in a system is assigned a full membership. In a normal operating condition, going to such extreme values is very unlikely. If a monitored value of a sensor is between the extreme values then the system will treat it as a failure with a certain degree of failure membership. The degree of failure membership for each monitored parameter will be estimated as follows:

$$Rf = \begin{cases} 1 - \frac{Y'_{12} - \hat{Y}}{Y'_{12} - Y}, & Y'_1 \leq \hat{Y} \leq Y'_2 \\ 1, & Y'_1 \geq \hat{Y} \geq Y'_2 \end{cases} \qquad [5.2]$$

where, $R_f$ is the degree of failure membership; $\hat{Y}$ represents monitored data for a particular time and $Y'_{12}$ represents both the minimum $(Y'_1)$ and the maximum $(Y'_2)$ values of the dependent variable. As both the minimum and maximum values are not possible to happen simultaneously, therefore, $Y'_{12}$ should be replaced with $(Y'_1)$ in case of minimum or $(Y'_2)$ in case of maximum. In addition, in the normal acceptable condition, the calculated degree of failure membership will be relatively smaller than their value in a failure condition. Therefore, increase in the values of degrees of failure memberships at different nodes / pipes from their values in normal condition will point out an anomaly in the system.

### 5.2.4 Node and Pipe Identification

Occurrence, in terms of location and amount, of leakage in a system is random. Due to leakage any monitored value could go beyond the two extreme values. To address this issue, coupled with the degree of leakage (failure membership), the index of leakage propensity (ILP) has been proposed. If a monitored value is within the range of the extreme values (inclusive) then the ILP is the same as the degree of leakage. However, if a monitored value is beyond the extreme values then the ILP is more than unity. The concept of ILP has been used to highlight the most likely leaky node as well as the most likely leaky pipe.

Leakage is pressure dependent demand (Lambert 2001). The presence of leakage in a node/ pipe not only changes the flow and pressure in the leaky node / pipe, and the downstream part of the WDS, it also changes the flow and pressure in the whole WDS to a certain extent. However, after the most significant impacts on leaky node, the 2nd most, the 3rd most and so forth, impacts will be observed on the adjacent 2nd, 3rd and so forth, nodes/ pipes of the leaky node, respectively.

If the leakage is large enough and located near the sensor location, the deviation of the monitored flow / pressure from the normal flow / pressure could go beyond the possible extreme values, and therefore, the ILP could be more than 1 in multiple nodes or pipes. However, the ILP will be the highest at the leaky node/ pipe. Therefore, the leaky node/pipe will be the one which has the highest ILP over the time after leakage. To ensure the leaky node or the leaky pipe is well identified, it is expected that the node with the second highest ILP / degree of leakage will be adjacent to the highest one. Therefore, after the identification of the leaky node/pipe, all the nodes/ pipes have been ranked based on their ILPs. In the case of pipes, it is expected that the identified most likely leaky pipe will be connected to the identified most likely leaky node. For example, in the case of a leaky node with four connected pipes, the 1st, 2nd, 3rd, and the 4th most likely leaky pipes will be connected to that node. From this topological information, the most likely leaky node and the most likely leaky pipe can be identified.

Installing pressure and flow sensors in all the key nodes is unlikely. In reality, in most WDSs, the numbers of the sensors are much lower than the number of nodes. In such situation, the above methodology could identify the presence of the leakage and the nearest sensor to the leakage. To highlight the nearest leaky node or pipe, additional investigation need to be carried out. For this case, an optimum number of sensors need to be installed in the WDS. This optimum number of sensors depends on the size of the WDS and the sizes of the leakage (leakage flow) to be detected. The number of the sensors should be such that the presence of the leakage must influence at least one sensor, and in the reverse way, the methodology will be able to detect only that size of leakage (or higher) which will be able to influence at least one sensor. In a DMA (district meter area) structured system, if there is only one flow and pressure meter at the DMA inlet, then this methodology cannot detect the leaking node. However, if the leakage search is conducted over the whole WDS (composed of multiple DMAs), then the algorithm can find out the leaky DMA. As a part of additional investigation, for a single leakage, an emitter has been modelled based on the assumed emitter coefficient and pressure exponent.

An Emitter is a device associated with junctions that model the flow through a nozzle or an orifice that discharges to the atmosphere (Rossman 2000). It can model the pressure depended demand (e.g., leakage) as an emitter flow in the form of Equation 5.3 (Wu et al. 2010).

$$q_{l,i}(t) = C_i\,[p_i(t)]^{N1} \tag{5.3}$$

where $q_{l,i}(t)$is the leakage flow rate at node $i$ at time $t$, $C_i$ is the discharge coefficient at node $i$, $p_i(t)$ is the nodal pressure at node $i$ at time $t$ and $N1$ is the emitter exponent or pressure exponent . The values of pressure exponent generally varies between 0.50 and 2.50, depending upon the type of leakage paths, network ages, corrosion types, pipe material and other network related factors (Farley and Trow 2003). A positive value of emitter coefficient will result in a leakage demand.

As discussed before, the presence of leakage will be identified based on the estimated degrees of leakage and the ILPs at sensor locations. To do that, the WDS with the normal values of independent parameters need to be solved putting an emitter coefficient in a node. This procedure needs to be repeated by putting the same emitter coefficient in all nodes. During each solution, the ILPs at sensor locations need to be estimated and compared (in terms of deviation) with the ILPs calculated when the first anomaly was detected. The absolute deviation of the ILPs at sensor locations will be minimal when the ILPs have been estimated from the network solution putting the emitter coefficient at the leaky node. The same comparison need to be carried out for all the sensors which can identify the presence of leakage. If the number of leakages in the system is more than one then the WDS needs to be analysed for the combination of multiple emitter exponents and nodes. However, the calculations will be minimal if the most likely leaky area is identified from the available sensor data. In that case, the network solutions, assigning emitter coefficients to nodes, will be required only on the nodes in the identified most likely leaky area and, hence, the computational efforts will be less. In a similar way, the most likely leaky pipe also needs to be identified. Based on the most likely leaky node and pipe information, the final leaky node/pipe will be identified.

## 5.3 Model Implementation

To demonstrate the applicability of the leakage detection and location methodology, the developed model based on the proposed methodology has been implemented and demonstrated through the example WDS used in section 3.3 in Chapter 3. The example WDS has 40 pipes with a total length of 19.5 km, connected by 27 nodes. Water is supplied by gravity from the two elevated reservoirs (reservoir 1 and reservoir 2) with the total head of 90 m, and 85 m, respectively. The lengths of the pipes vary from 100 m to 680 m, and the diameters of the pipes vary from 200 mm to 700 mm. Base demands at different nodes varies from 50 l/s to 100 l/s and demand multipliers ranges from 0.38 at 5am to 1.46 at 9 am. Detail information on pipe length, diameter, roughness coefficient, nodal connectivity, and nodal hourly base demand and demand multipliers and two reservoirs head have been provided in Table 3.6 in Chapter 3.

The WDS has been considered as an undamaged system, and all the parameter values are considered as calibrated values in normal condition. The parameters such as roughness coefficients, nodal demands, reservoir water levels, pipe diameters, length of the pipes, and head loss coefficients are uncertain. For this case study, only the roughness coefficients, nodal demands and the reservoir water levels have been taken as uncertain independent parameters. According to the procedure described in Section 5.2.1, the minimum, the most likely and the maximum values of the independent parameters are selected. As assumed by Gupta and Bhave

(2007), for the reservoir levels ±0.5 m, for the roughness coefficients ±5, and for the nodal base demands ± 5% deviations from their normal values have been considered to estimate the two extreme values of those independent parameters. Coupling the procedure described in Section 5.2.2 with EPANET determines minimum, most likely and the maximum values of dependent parameters at all nodes and pipes over a period of 24 hours.

Based on the estimated normal, minimum and maximum values of the dependent parameters, a set of fuzzy numbers has been derived for all nodes and pipes over the period of 24 hours. Artificially created pressure and flow sensor data are fed into the developed model to diagnose any anomalies (e.g., the leakage) in the WDS.

### 5.3.1 Leakage Data Preparation

As the study has been carried out on an example WDS, the sensor data or monitored data are prepared by simulating the WDS under a leaky condition. To represent the leakage in a WDS, an emitter coefficient and a pressure exponent has been incorporated at a node of the calibrated hydraulic model. To represent randomness (both in terms of size and location) in the leakage an arbitrary emitter coefficient of 0.95 and a pressure exponent of 1.10 have been randomly incorporated into node 20. Although, the emitter coefficient is completely random, the value of pressure exponent N1 (1.1) has been selected to represent a medium aged network. It is noted that the value of pressure exponent of a network can be estimated from a standard pressure step test (a standard test carried out at the time of minimum night flow to estimate the leakage).

The emitter generates pressure dependent leakage demand to node 20 which is in addition to the base demand. After the incorporation of leakage demand, the WDS has been solved for the normal operating condition. The solutions for different nodes and pipes for this WDS represents monitored/ sensor data for all nodes and pipes under the leaky condition due to leakage at node 20).

In the case of limited number of sensors, arbitrarily five pressure sensors have been placed at the nodes no. 4, 7, 9, 17, and 19 so that those sensors can cover the whole WDS. Although, in this study, the number of sensors and their placement locations has not been optimized, it would be preferable to find the optimal number of sensors and their locations in the WDS. To represent the leaky condition of the WDS, the emitter coefficient has been applied arbitrarily to node no. 13.

The WDS has been simulated in the normal condition, and the simulated node and pipe results for nodes no. 4, 7, 9, 17, and 19 represent the pressure sensor data for those nodes.

### 5.3.2 Leakage Detection

After estimating the degrees of leakage and the ILPs, it is observed (Table 5.2) that, in certain times of the day, node 25 has a degree of leakage of 1 and the ILPs higher than 1 which indicate the presence of anomaly in the WDS. However, if the leakage to be detected has a little flow rate, no ILP will be higher than 1. In that case, the presence of leakage can be identified from the maximum value of the degrees of leakage / ILPs and their deviations from their normal values. On the other hand, if the leakage is large, it is anticipated that more than one node could have ILPs greater than 1. In that case, the most likely location of the leakage will correspond to the maximum ILP location. As an example, Table 5.2 shows the degree of leakage and the ILPs in node 13 and node 25 over 24 hours of a typical day.

Table 5.2: Typical degrees of leakage memberships and the associated ILPs

| Time (hour) | Node 13 | | Node 25 | |
|---|---|---|---|---|
| | μ(x) | ILP(x) | μ(x) | ILP(x) |
| 0-2 | 0.96 | 0.96 | 1.00 | 3.06 |
| 2-4 | 1.00 | 1.07 | 1.00 | 5.57 |
| 4-6 | 1.00 | 1.05 | 1.00 | 5.77 |
| 6-8 | 0.86 | 0.86 | 1.00 | 2.21 |
| 8-10 | 0.27 | 0.27 | 0.59 | 0.59 |
| 10-12 | 0.31 | 0.31 | 0.69 | 0.69 |
| 12-14 | 0.67 | 0.67 | 1.00 | 1.70 |
| 14-16 | 0.76 | 0.76 | 1.00 | 2.05 |
| 16-18 | 0.50 | 0.50 | 1.00 | 1.19 |
| 18-20 | 0.23 | 0.23 | 0.49 | 0.49 |
| 20-22 | 0.47 | 0.47 | 1.00 | 1.10 |
| 22-24 | 0.61 | 0.61 | 1.00 | 1.52 |

If the changes in flow or pressure are only due to the variation of base water demand or changes in other independent parameters, then the degree of leakage and the ILPs will be 1 or less, as the values of the independent parameters cannot go beyond their extreme values. In a rare case, if any high abnormal demand like fire flow exists in the system, it is unlikely to continue for a whole day or longer. From Table 5.2, it can be concluded that there is a possibility for an anomaly which has increased the degrees of leakage up to 1 and the ILPs higher than 1. However, in case of a limited number of sensors, the degrees of leakage at the sensor nodes could be smaller than 1 if the leakage is located too far from the sensor nodes to influence them. In that case, the variation of the total system inflow has to be checked. If the variation of the system inflow is unexpected, then the leakage search should be carried out even with the degree of leakage membership less than 1.

### 5.3.3 Leakage Location

Having any node or pipe with a degree of leakage membership 1 and the ILP greater than 1, or having any node or pipe with a significant deviation from the normal degree of leakage and the ILP (in case of small leakage), does not indicate the presence of leakage at that node or pipe, rather indicates an abnormality in the system. For example, in Table 5.2, most of the times, node 25 has a degree of leakage as well as the ILPs greater than 1. It does not guarantee that node 25 is the leaky node. Anomalies could be at that node or elsewhere in the WDS. However, the most influenced degree of leakage / ILP location will be at the leaky node/pipe and then the nearby nodes/pipes. Figure 5.4 shows the ILPs at different nodes.

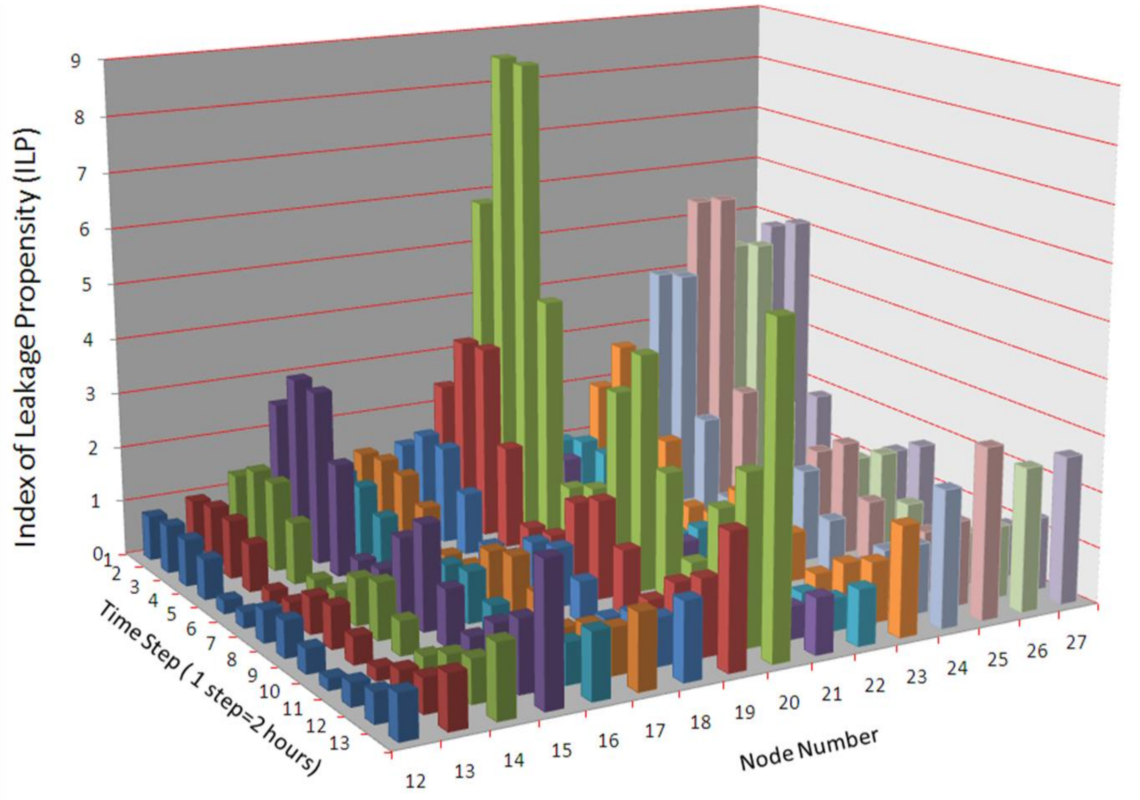



Figure 5.4: ILPs at different nodes (different color represents ILPs in different nodes)

Figure 5.4 shows that the maximum observed ILPs over the time are always at node 20 which represents the most influenced node. The most likely, the 2$^{nd}$, the 3$^{rd}$, and the 4$^{th}$ most likely leaky nodes have been identified as no. 20, 25, 19, and 15, respectively. Table 5.3 provides the ranking order of the top four most likely leaky nodes and pipes.

Table 5.3: Identification of the most likely leaky nodes and pipes in order

| Time (hour) | Most likely leaky pipe no. | | | | Most likely leaky node no. | | | |
|---|---|---|---|---|---|---|---|---|
| | First | Second | Third | Fourth | First | Second | Third | Fourth |
| 2 | 29 | 25 | 34 | 37 | 20 | 25 | 15 | 19 |
| 4 | 29 | 25 | 34 | 37 | 20 | 25 | 27 | 26 |
| 6 | 29 | 25 | 34 | 37 | 20 | 25 | 27 | 26 |
| 8 | 29 | 25 | 34 | 37 | 20 | 15 | 25 | 19 |
| 10 | 29 | 25 | 34 | 28 | 20 | 19 | 25 | 15 |
| 12 | 29 | 25 | 34 | 28 | 20 | 19 | 25 | 15 |
| 14 | 29 | 25 | 34 | 28 | 20 | 25 | 19 | 15 |
| 16 | 29 | 25 | 34 | 28 | 20 | 15 | 25 | 19 |
| 18 | 29 | 25 | 34 | 28 | 20 | 25 | 19 | 15 |
| 20 | 29 | 25 | 34 | 28 | 20 | 19 | 25 | 15 |
| 22 | 29 | 25 | 34 | 28 | 20 | 25 | 19 | 15 |
| 24 | 29 | 25 | 34 | 28 | 20 | 25 | 19 | 15 |

Similarly, the most likely leaky pipes are in the ranking order of pipe no. 25, 34, 28, and 37. From the topology of the identified pipes and node shown in Figure 3.9, it is seen that the pipes 29, 25, and 34 are connected to node 20. It can also be observed that node 20 is connected with node 19, 15, and 25 by pipe 29, 25, and 34, respectively. Therefore, it is concluded that the most likely leaky node is no. 20 and the most likely leaky pipe is pipe no. 29.

Table 5.4: Degree of leakage membership for a small leak at node 13

| Time, hr | Node 8 | Node 12 | Node 13 | Node 14 | Node 18 |
|---|---|---|---|---|---|
| 0-2 | 0.09 | 0.11 | 0.17 | 0.13 | 0.13 |
| 2-4 | 0.09 | 0.12 | 0.20 | 0.11 | 0.15 |
| 4-6 | 0.09 | 0.12 | 0.20 | 0.11 | 0.15 |
| 6-8 | 0.08 | 0.11 | 0.16 | 0.12 | 0.11 |
| 8-10 | 0.06 | 0.06 | 0.08 | 0.06 | 0.06 |
| 10-12 | 0.06 | 0.07 | 0.08 | 0.06 | 0.07 |
| 12-14 | 0.08 | 0.10 | 0.13 | 0.10 | 0.10 |
| 14-16 | 0.08 | 0.10 | 0.14 | 0.11 | 0.11 |
| 16-18 | 0.08 | 0.09 | 0.11 | 0.08 | 0.09 |
| 18-20 | 0.06 | 0.06 | 0.07 | 0.06 | 0.06 |
| 20-22 | 0.08 | 0.08 | 0.10 | 0.08 | 0.08 |
| 22-24 | 0.08 | 0.10 | 0.12 | 0.09 | 0.09 |

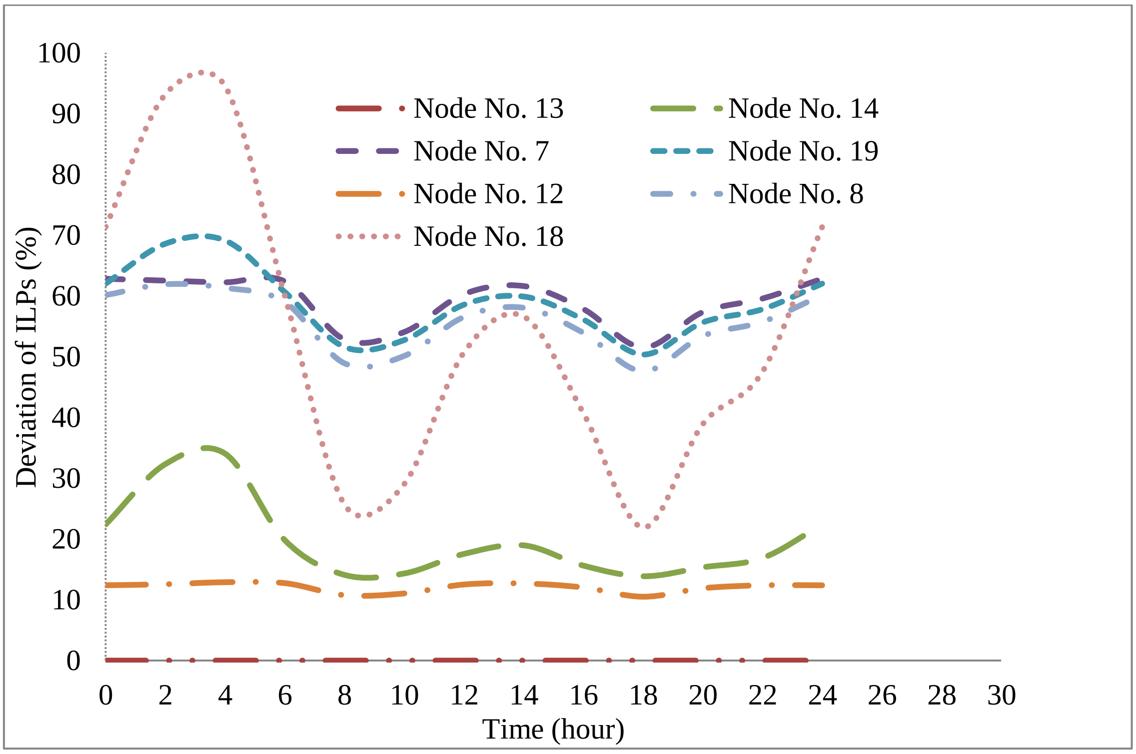



Figure 5.5: Deviations of ILPs at Sensor at Node No. 19 over time (limited number of sensors)

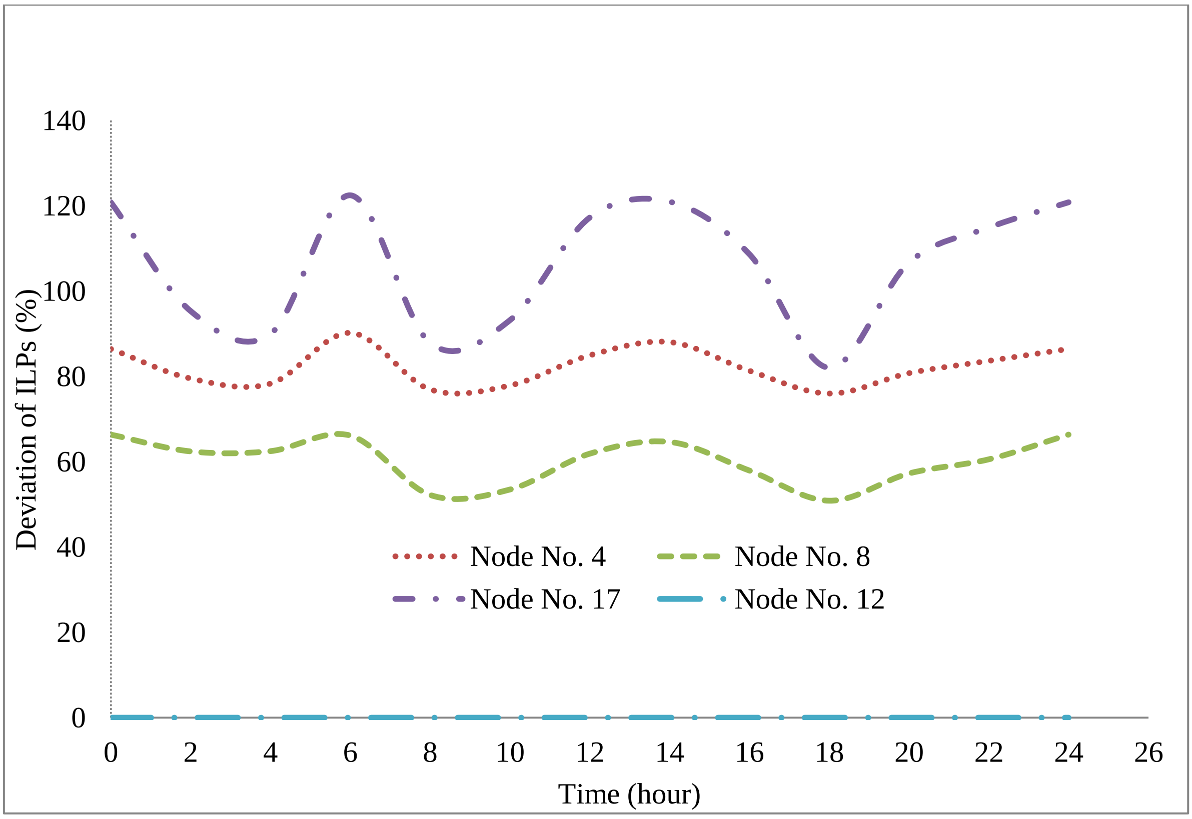



Figure 5.6: Deviations of ILPs at Sensor at Node No. 17 over time for a small leak

To investigate the sensitivity of the leakage volumes, similar analysis has been carried out using a small leakage modeled using an emitter coefficient of 0.1 at node 13. Table 5.4 shows the degrees of leakage / ILPs at node 13 and surrounding four nodes during 24 hours of a typical day. Table 5.4 shows that the degrees of leakage / ILPs at the node 13 are higher than the surrounding nodes at all times which confirm the anomaly at the node 13. As the values of the degrees of leakage are lower than 1, the utility managers need to decide whether they will take an action or not, to remove that anomaly.

As stated earlier, in case of a limited number of sensors, five pressure sensors have been placed at the nodes no. 4, 7, 9, 17, and 19. The ILPs at sensor locations under the leaky conditions have been estimated by putting an emitter coefficient of 0.95 arbitrarily at node 13. Thereafter, the WDS for the normal condition has been solved considering the same emitter coefficient (0.95) but in different nodes which produces $n_d$ solutions, where $n_d$ is the number of the nodes. During each solution, the ILPs have also been estimated at different sensor locations. The estimated ILPs for each solution have been compared with the ILPs calculated at each sensor location just after the identification of leakage (for an emitter coefficient of 0.95 at node 13). It was mentioned earlier that the deviation is minimal when the ILPs are calculated assigning the emitter coefficient at the leaky node (i.e., node 13). Figure 5.5 shows the deviation of ILPs over time at node 19 assigning the emitter coefficient at different nodes. From Figure 5.5, it is apparent that the deviation of the ILPs at different times is 0% while the emitter coefficient was assigned at node 13 which indicates the most likely leakage location.

To investigate the sensitivity of the leakage volumes, locations, sensor number and their locations, similar analysis has been carried out for a small leakage modeled using an emitter coefficient of 0.1 at node 12. In this case, four sensors have been placed at the node 4, 8, 14, and 17. After locating the nearest sensor to leakage (in this case at node 17), the ILPs at this node have been compared by assigning the emitter coefficient at different nodes. Figure 5.6 shows the deviations of the ILPs at the sensor node no. 17 over the time for a small leak. From Figure 5.6, it is apparent that, even for a small leak, the deviation of the ILPs in different times is 0% while the emitter coefficient was assigned at the node 12 which indicates the most likely leakage location.

## 5.4 Summary

This section of research has presented a novel methodology for leakage detection and diagnosis in WDS. The proposed methodology considers different WDS influencing factors as uncertain independent parameters. The uncertainties of the independent parameters are modeled using fuzzy numbers. Using the developed methodology, and based on monitored pressure and flow, the degree of leakage as well its severity in terms of the index of leakage propensity (ILP) has been estimated. Based on the developed methodology, a leakage detection and location system has been developed using MATLAB. The developed model has been implemented on an example WDS to demonstrate its applicability. From the analysis, it can be seen that the developed model can detect the leakage and diagnose the exact location of the leakage.

The developed model can be used for any real WDS by modifying appropriate parameters. Indeed, the developed model should be updated based on any specific condition of any particular WDS, especially, the ranges of different independent influencing factors. Moreover, the developed methodology can be extended to similar problems such as water quality failure detection. Although the proposed methodology can identify the leakage, in case of multiple leakages with limited number of sensors, the computational efforts will be higher. The developed model can be integrated with EPANET as an add-on, which will increase its capacity to be used for leakage detection and diagnosis. .

# CHAPTER 6 WATER QUALITY FAILURE POTENTIAL MODEL

A version of this chapter has been submitted for publication to the Journal of Water Resource Management on 19th September 2011 with the title "*Evaluating Water Quality Failure Potential in Water Distribution Systems: A Fuzzy-TOPSIS-OWA-based Methodology"* (Islam at al. 2011c).

## 6.1 Background

Water quality in distribution system warrants maximum attention to ensure a safe drinking water for the consumers. However, the current operation & maintenance (O&M) and management practices for WDS don't necessarily fully address the vulnerability of water to be contaminated or deteriorated (US EPA 2006). In Chapter 2, a review of different water quality failure studies have been reported. In spite of significant efforts, hundreds of boil water advisories everyday across Canada, and elsewhere highlights the importance of water quality issues. Table 1.1 shows the vignette of national boil water advisories of a typical day (24th August, 2011) in Canada (Water 2011). From this table, it is evident that in a typical day in Canada, water from 50 WDSs is not consumable and water from 1,199 WDSs suggested boiling before consumption. There are numerous reasons that may compromise or cause failure of water quality. Rapidly increasing urban sprawl, deterioration of source water quality, aging of water distribution infrastructure and poor O&M and management practices have significant impacts on the water quality (Charron et al. 2004). In USA, since 1940, up to 40% of reported waterborne disease outbreaks have been linked to the WDS problems (US EPA 2006). Accidental intrusion or malicious activities may also contribute failure of water quality in the distribution system.

A WDS is a spatially distributed infrastructure comprises of hundreds (based on size) of kilometers of buried pipes, joints, intermediate tanks, and consumer fixtures and fittings. Due to the heterogeneity of different components and their materials, ages, construction quality, the occurrences of multiple physical / chemical / biological processes over the time, and the lack of timely data, it is very difficult to completely understand the water quality deterioration process in a WDS. The water quality can be comprised at any time and at any point without being understood and noticed. Being pressurized and continuous flow system, contamination/ deterioration at a single point may affect the water quality in whole or a significant part of a

WDS. Sadiq et al. (2008) categorized the mechanisms of water deterioration and contamination in a WDS as follows:

- intrusion of contaminants through the failed or less integrated components of the WDS (e.g., pipe joints and cross-connections)
- regrowth of microbes in the pipes and the distribution storage tanks
- microbial (and/or chemical) breakthroughs at the water treatment plants
- formation of disinfectant by-products (DBP) and the loss of disinfectants
- residual chemicals from leaching of chemicals or corrosion products from system components (e.g., pipes, tanks, and liners)
- failure of the water treatment plants
- accidental intrusion or malicious activities and
- the permeation of organic compounds through various plastic components of the system.

Whatever might be the reason for the failure, the likelihood and consequence of the failure can be reduced to an acceptable limit, if the prognostic analysis and necessary preventive measures are taken on time. Therefore, it is an open challenge to the engineers to identify the potential occurrence and the possible reasons for the water quality failure (WQF) before the occurrence.

In this model, using fuzzy set theory coupled with multi-criteria decision-making (MCDM) techniques - TOPSIS (technique for order preference by similarity to ideal solution) and OWA (ordered weighted averaging) operators - a methodology has been developed to estimate WQF potential in a WDS and identify contribution of different parameters. As stated earlier, the term ‘potential’ for WQF has been used to refer the ‘possibility’ or ‘likelihood’ of WQF occurrence. The scale of ‘potential’ is defined as a continuous interval of [0, 1] or [0, 100%]. The terms ‘probability’, ‘possibility’, ‘risk’ and even ‘likelihood’ have been intentionally not used to avoid confusion. A 100% WQF potential of a WDS refers to the condition that the water in the distribution system has potential to become undrinkable. If the WQF potential is estimated to be 100%, it refers to the situation that failure in inevitable and the supplied water is unacceptable to drink.

Fuzzy set theory (Zadeh 1965) has been used to address the uncertainties involved in the modelling of different water quality parameters and their interrelationships in the forms of subjectivity, vagueness, and impreciseness. The TOPSIS has been proposed to evaluate the influences of different WQF causal parameters to WQF potential. In TOPSIS, alternatives are compared with the positive and the negative ideal solutions to evaluate the influences of water quality parameters. To aggregate the impacts of different water quality parameters, OWA operator introduced by Yager (1988) has been used. A simplified example has been used to demonstrate developed methodology and finally, a full scale model has been tested for a WDS in Quebec City (Canada) based on available data.

## 6.2 Materials and Methods

Figure 6.1 shows the conceptual methodology for the development of WQF potential model.

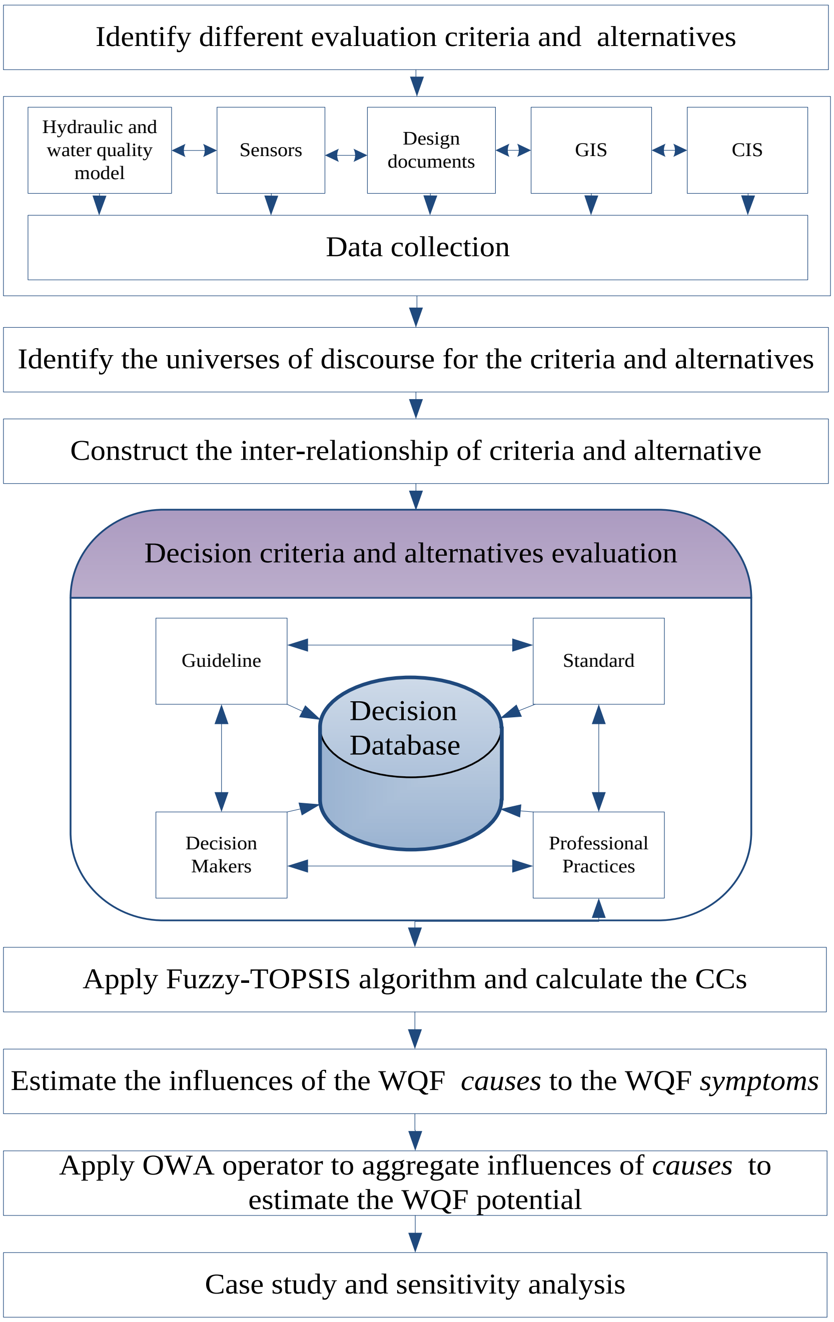



Figure 6.1: Conceptual methodology for the development of WQF potential model

The methodology requires identification of different influencing factors (parameters), their interrelationship, and the aggregation mechanism to determine the effects of different factors to predict the WQF potential. Two types of parameters have been identified, namely, the *symptoms* of WQF (hereafter termed "*symptoms*") such as taste & odor, and the *causes* of WQF (hereafter termed "causes") such as turbidity & free residual chlorine. The effects of these *causes* are manifested through the *symptoms*. The *causes-symptoms* relationships were evolved based on different regulatory guidelines and standards, professional experience, and decision makers' attitudes. The evaluation of influences of different parameters (for both *symptoms* and *causes*) to WQF are subjected to imprecision and vagueness. Elicited opinions from experts expressed in qualitative terms and have been modelled using fuzzy numbers.

As the linguistic experts' opinions are subjective, vague, and imprecise in nature, fuzzy set theory has been used. To express linguistic experts' opinion, triangular fuzzy numbers (TFNs) or trapezoidal fuzzy numbers (ZFNs) can be used (Figure 3.4). Equations 3.2 and 3.3 (Chapter 3) have been used to model the TFN and ZFN. The values of a, b, and c, for different experts' opinion are defined based on reviewed literature and experts' suggestions. Definitions of qualitative expert's opinion have been shown in Table 6.1.

Table 6.1: Definition of linguistic evaluation

| Weight Importance of Criteria | | Ratings for the alternatives | |
|---|---|---|---|
| Very Low (VL) | (0,0,0.1) | Very Good (VG) | (0,0,01) |
| Low (L) | (0,0.1,0.3) | Good (G) | (0,01,03) |
| Medium Low (ML) | (0.1,0.3,0.5) | Medium Good (MG) | (01,03,05) |
| Medium (M) | (0.3,0.5,0.7) | Fair (F) | (03,05,07) |
| Medium High(MH) | (0.5,0.7,0.9) | Medium Bad(MB) | (05,07,09) |
| High (H) | (0.7,0.9,1.0) | Bad (B) | (07,09,10) |
| Very High(VH) | (0.9,1.0,1.0) | Very Bad(VB) | (09,10,10) |

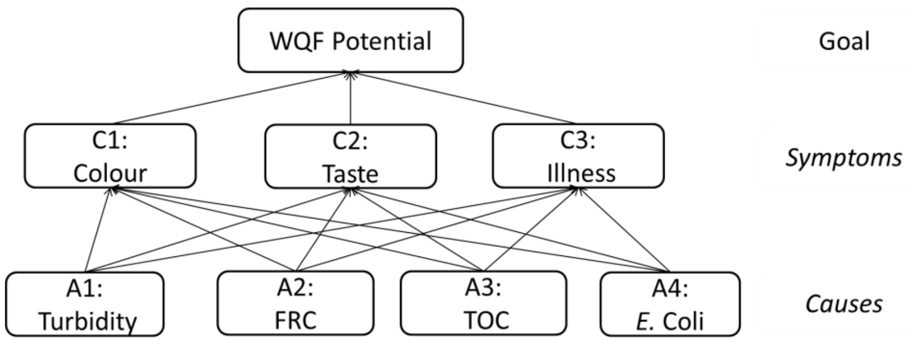
Multi-criteria decision-making technique, TOPSIS has been used to evaluate the influence of different causal parameters on different *"symptoms"*. To aggregate the impacts of different *causes*, an OWA operator has been used. Details of the proposed methodology have been provided in the following sections. Based on the developed model, to evaluate WQF potential, data are to be collected for the identified parameters. Data can be collected from different sensors, geographical information system (GIS), customer information system (CIS), design documents, existing hydraulic and water quality models and so forth.

The development of the proposed methodology has been demonstrated using a simplified example of WQF potential evaluation. For this simplified example, four parameters are considered as possible alternative *causes* of WQF and three *symptoms* are used as performance criteria to evaluate the impact of *causes* to overall WQF potential.

**Step 1. Forming a multi-expert team:** At the beginning, a group of experts are to be consulted. It is anticipated that the experts have an in-depth understanding of different *symptoms* (criteria) and *causes* (alternatives) and can establish causality among them. For this study, three experts working in water distribution modelling field has been consulted.

**Step 2. Defining *causes* and *symptoms*:** For the simplified example, four parameters ($A_{i,}$ i=1, 2 …n; n=4), namely, turbidity (A1), free residual chlorine (A2), Total Organic Carbon, TOC (A3) and *E. coli* (A4) are used as possible alternatives, i.e., *causes* of WQF. Three *symptoms* ($C_{j,}$ j = 1, 2 …m; m = 3) namely, colour (C1), taste (C2), and illness (C3) are used as performance criteria to evaluate the impact of *causes* on overall WQF potential. In case of complex full scale problem, number of alternatives and criteria could be higher and an extensive literature survey will help identify them.

**Step 3. Developing interrelationships among *symptoms* and *causes*:** Figure 6.2 defines the interrelationships among different *causes* and *symptoms*. The hierarchical structure consists of three levels: the goal (identifying the WQF potential) at the first level, the *symptoms* (criteria) at second level) and the *causes* (alternative) at the third level. This relationship has been developed considering each *cause* has influences to each *symptom*. In reality, if no such relationship exists (e.g., TOC can have very limited impact on illness), experts' opinion will evaluate as minimal influences in their evaluation.




FRC=Free residual chlorine (mg/l); TOC=Total organic carbon (mg/l)

Figure 6.2: Interrelationship of different *causes* and *symptoms*

**Step 4. Collecting multi-expert opinions:** For evaluating importance of criteria, decision makers evaluate the weight of each criterion with respect to the overall goal whereas for the rating of alternatives, the decision makers evaluate each alternative with respect to each criterion. For the illustrative example, Table 6.2 shows the importance weight of the criteria provided by three experts. As per definition in Table 6.1, VH indicates maximum importance and VL indicates minimum importance.

Table 6.2: Importance weights of criteria

| Criteria | DM1 | DM2 | DM3 |
|---|---|---|---|
| Color | H | H | MH |
| Taste | H | MH | H |
| Illness | VH | VH | VH |

DM= Decision maker

Table 6.3: Dynamic systems for experts' opinion

| Criteria / Alt. | Range | DM1 | | | DM2 | | | DM3 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Color | Taste | Illness | Color | Taste | Illness | Color | Taste | Illness |
| Turbidity, NTU | 0-0.1 | VG | VG | VG | VG | VG | VG | VG | VG | VG |
| | 0.1-.3 | G | VG | G | G | VG | G | G | VG | VG |
| | 0.3-0.5 | G | G | G | G | VG | MG | VG | G | MG |
| | 0.5-0.7 | MG | G | MG | G | G | MG | G | G | MG |
| | 0.7-1 | F | MG | MG | F | MG | F | F | MG | MG |
| | 1-1.5 | MB | F | F | MB | F | MB | MB | F | MB |
| | 1.5+ | B | MB | MB | B | MB | B | B | MB | B |
| TOC, mg/l | 0-0.5 | VG | VG | VG | VG | VG | VG | VG | VG | VG |
| | 0.5-1 | G | G | MG | G | G | MG | G | G | MG |
| | 1-2 | MG | G | F | MG | G | F | MG | G | F |
| | 2-5 | F | F | MB | F | F | MB | F | F | MB |
| | 5+ | MB | MB | B | MB | MB | B | MB | B | B |
| Free Residual Chlorine, mg/l | 0-0.2 | VG | VG | MG | VG | VG | MG | VG | VG | MG |
| | 0.2-0.5 | VG | VG | VG | VG | VG | VG | VG | VG | VG |
| | 0.5-1 | VG | MG | VG | VG | MG | VG | VG | MG | VG |
| | 1-2 | G | B | VG | VG | B | VG | G | B | VG |
| | 2-5 | MG | B | VG | MG | B | VG | G | B | VG |
| | 5+ | MG | VB | VG | MG | VB | VG | MG | VB | VG |
| E. Coli, no | 0 | VG | VG | VG | VG | VG | VG | VG | VG | VG |
| | >0 | VG | G | VB | VG | G | VB | VG | G | VB |

Water quality in a WDS varies with respect to space and time (Berry et al. 2006; Francisque et al. 2009). Therefore, to evaluate WQF potential for a continuously changed system, a dynamic system for experts' opinion has been created containing experts' opinion for the rating of the alternatives for all possible values for the alternatives. Table 6.3 shows the rating of the alternatives with respect to each criterion provided by three experts. As per definition in Table 6.1, VB indicates maximum influence rating whereas VG indicates minimum influences.

To demonstrate the extraction of expert opinion from the dynamic system, consider a water sample from a consumer tap whose measured turbidity, TOC, Free residual chlorine and E. coli counts are 0.2 mg/l, 0.7 mg/l, 0.2 mg/l and 0, respectively. Based on the dynamic expert system (Table 6.4), the rating of the alternative for this sample has been sown in the Table 6.4.

Table 6.4: Rating of the alternatives

| Alternatives | Value | Criteria | Experts | | |
|---|---|---|---|---|---|
| | | | DM1 | DM2 | DM3 |
| Turbidity, NTU | 0.2 | Color | G | G | G |
| TOC, mg/l | 0.7 | | G | G | G |
| Free residual chlorine, mg/l | 0.3 | | VG | VG | VG |
| E. coli, no | 0 | | VG | VG | VG |
| Turbidity, NTU | 0.2 | Taste | VG | VG | VG |
| TOC, mg/l | 0.7 | | G | G | G |
| Free residual chlorine, mg/l | 0.3 | | VG | VG | VG |
| E. coli, no | 0 | | VG | VG | VG |
| Turbidity, NTU | 0.2 | Illness | VG | G | VG |
| TOC, mg/l | 0.7 | | MG | MG | MG |
| Free residual chlorine, mg/l | 0.3 | | VG | VG | VG |
| E. coli, no | 0 | | VG | VG | VG |

**Step 5. Aggregating weights of a criterion and ratings of an alternative:** To form a weight matrix and a decision matrix, the linguistic weights of the criteria and the ratings of an alternative by different experts expressed in terms of TFNs have been aggregated. If a committee of experts has *N* members and the fuzzy weight of $j^{th}$ criteria is, $\tilde{w}_j = (\tilde{w}_{ja}, \tilde{w}_{jb}, \tilde{w}_{jc})$ then the fuzzy aggregated weight is calculated using the following equations (Equations [6.1, 6.2, and 6.3 ]).

$$\tilde{w}_{ja} = \frac{1}{N}(\tilde{w}^1_{ja} + \tilde{w}^2_{ja} + \tilde{w}^3_{ja} + .......... + \tilde{w}^N_{ja}) \quad [6.1]$$

$$\tilde{w}_{jb} = \frac{1}{N}(\tilde{w}^1_{jb} + \tilde{w}^2_{jb} + \tilde{w}^3_{jb} + .......... + \tilde{w}^N_{jb}) \quad [6.2]$$

$$\tilde{w}_{jc} = \frac{1}{N}(\tilde{w}^1_{jc} + \tilde{w}^2_{jc} + \tilde{w}^3_{jc} + .......... + \tilde{w}^N_{jc}) \quad [6.3]$$

For the illustrative example, the minimum, the most likely and the maximum values of the fuzzy aggregated weight of the colour criteria will be $\tilde{w}_{ja} = \frac{1}{3}(0.7 + 0.7 + 0.5) = 0.633$ ,

$\tilde{w}_{jb} = \frac{1}{3}(0.9 + 0.9 + 0.7) = 0.833$, $\tilde{w}_{jc} = \frac{1}{3}(1.0 + 1.0 + 0.9) = 0.967$ , respectively. In a similar fashion, the aggregated fuzzy weight for taste and illness will be (0.633, 0.833, 0.967) and (0.9, 1, 1), respectively.

In a similar fashion, if the rating of the $i^{th}$ alternative for $j^{th}$ criteria is, $\tilde{x}_{ij} = (x_{ija}, x_{ijb}, x_{ijc})$ then the aggregated rating can be expressed with the following equations (Equations 6.4,6.5, and 6.6):

$$x_{ija} = \frac{1}{N}\left[x_{ija}^{1} + x_{ija}^{2} + .... + x_{ija}^{N}\right], \qquad [6.4]$$

$$x_{ijb} = \frac{1}{N}\left[x_{ijb}^{1} + x_{ijb}^{2} + .... + x_{ijb}^{N}\right] \qquad [6.5]$$

$$x_{ijc} = \frac{1}{N}\left[x_{ijc}^{1} + x_{ijc}^{2} + .... + x_{ijc}^{N}\right] \qquad [6.6]$$

Continuing the illustrative example, the minimum, the most likely and the maximum value of the fuzzy aggregated rating of the turbidity with respect color will be , $x_{ija} = \frac{1}{3}(0 + 0 + 0) = 0$

$x_{ijb} = \frac{1}{3}(0 + 1 + 0) = 0.333$ ; $x_{ija} = \frac{1}{3}(1 + 3 + 1) = 1.667$ respectively.

Ratings for all the *causes* against each *symptom* can be calculated and populated in decision matrix shown in Step 6.

**Step 6. Constructing and normalizing a fuzzy decision matrix:** From the aggregated ratings of alternatives and weights of the criteria, a decision and a weight matrix have been constructed as follows:

$$\tilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & - & - & \tilde{x}_{1j} & - & - & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & - & - & \tilde{x}_{2j} & - & - & \tilde{x}_{2n} \\ - & - & - & - & - & - & - & - \\ - & - & - & - & - & - & - & - \\ \tilde{x}_{i1} & \tilde{x}_{i2} & - & - & \tilde{x}_{ij} & - & - & \tilde{x}_{in} \\ - & - & - & - & - & - & - & - \\ - & - & - & - & - & - & - & - \\ \tilde{x}_{m1} & \tilde{x}_{m2} & - & - & \tilde{x}_{mj} & - & - & \tilde{x}_{mn} \end{bmatrix} \qquad [6.7]$$

$$\tilde{W} = \begin{bmatrix} \tilde{w}_1 & \tilde{w}_2 & - & - & \tilde{w}_j & - & - & \tilde{w}_n \end{bmatrix} \qquad [6.8]$$

where $\tilde{x}_{ij}$ is the aggregated fuzzy rating of $i^{th}$ alternative with respect to $j^{th}$ criterion and $\tilde{w}_j$ is the aggregated fuzzy weight of $j^{th}$ criterion with respect to the overall goal and, i=1,2,3……m, j=1,2,3……n.

For the illustrative example, Table 6.5 shows the aggregated weight of criteria (first row) and rating of alternatives (other than first row) calculated as per Step 5.

Table 6.5: Aggregated fuzzy weight of criteria and rating of alternatives

| Weight / Alternatives | C1 | C2 | C3 |
|---|---|---|---|
| Weight | (0.63,0.83,0.97) | (0.63,0.83,0.97) | (0.90,1,1) |
| A1 | (0, 1, 3) | (0, 0, 1) | (0, 0.33, 1.67) |
| A2 | (0, 1, 3) | (0, 1, 3) | (1, 3, 5) |
| A3 | (0, 0, 1) | (0, 0, 1) | (0, 0, 1) |
| A4 | (0, 0, 1) | (0, 0, 1) | (0, 0, 1) |

C= Criterion (*symptom*); A= Alternative (*cause*)

The calculated weight matrix, $\tilde{W}$, is already normalized, no further normalization is necessary. However, to obtain a normalized decision matrix, $\tilde{R}$, the decision matrix, $\tilde{D}$ is to be normalized. The normalization has been carried out by the linear scale transformation in the following forms:

$$\tilde{R} = [\tilde{r}_{ij}]_{m \times n} \qquad [6.9]$$

where, $\tilde{r}_{ij}$ normalized rating and the normalization has been carried out using the following equations:

$$\tilde{r}_{ij} = (\frac{x_{ija}}{d_j^*}, \frac{x_{ijb}}{d_j^*}, \frac{x_{ijc}}{d_j^*}),\ d_j^* = \max(x) \quad [6.10]$$

where, *i, j, a, b,* and *c* have their usual meaning as defined earlier.

For the illustrative example, Table 6.6 shows the normalized decision matrix with all the values in an exhaustive range [0, 1].

Table 6.6: Fuzzy normalized decision matrix

| Alternatives | C1 | C2 | C3 |
|---|---|---|---|
| A1 | (0, 0.33, 1) | (0, 0, 0.33) | (0, 0.07, 0.33) |
| A2 | (0, 0.33, 1) | (0, 0.33, 1) | (0.2, 0.6, 1) |
| A3 | (0, 0, 0.33) | (0, 0, 0.33)) | (0, 0, 0.2) |
| A4 | (0, 0, 0.33) | (0, 0, 0.33) | (0, 0, 0.2) |

The fuzzy weighted normalized decision matrix calculated using the equations as follow:

$$\tilde{V} = [\tilde{v}_{ij}]_{m\times n} \quad , \quad i=1,2,3\ldots\ldots m,\ j=1,2,3\ldots\ldots n \quad [6.11]$$

where $\tilde{v}_{ij} = \tilde{r}_{ij}(.)\tilde{w}_j$ [6.12]

Element of $\tilde{v}_{ij}$ is normalized fuzzy number and their elements are in the range of [0, 1]. For the illustrative example, Table 6.7 shows the fuzzy weighted normalized decision matrix.

Table 6.7: Fuzzy weighted normalized decision matrix

| Alternatives | C1 | C2 | C3 |
|---|---|---|---|
| A1 | (0, 0.28, 0.97) | (0, 0, 0.32) | (0, 0.07, 0.33) |
| A2 | (0, 0.28, 0.97) | (0, 0.28, 0.97) | (0.18, 0.6, 1) |
| A3 | (0, 0, 0.32) | (0, 0, 0.32) | (0, 0, 0.20) |
| A4 | (0, 0, 0.32) | (0, 0, 0.32) | (0, 0, 0.20) |

**Step 7. Determining the FPIS and the FNIS:** The positive ideal solution (PIS) aims to maximize the benefits attributes and minimizes the cost attributes. The negative ideal solution (NIS) does the reverse; it minimizes the benefit attributes and maximizes the cost attributes. An alternative that is closer to the PIS and farther from the NIS is the best solution (Santos and Camargo 2010). The fuzzy positive ideal solution (FPIS, $A^+$) and the fuzzy negative ideal solution (FNIS, $A^-$) are defined as follows:

$$A^{+} = \{\tilde{v}_1^{+}, \tilde{v}_2^{+}, \tilde{v}_3^{+}, ..., \tilde{v}_j^{+}\} \quad [6.13]$$

$$A^{-} = \{\tilde{v}_1^{-}, \tilde{v}_2^{-}, \tilde{v}_3^{-}, ..., \tilde{v}_j^{-}\} \quad [6.14]$$

where, $\tilde{v}_j^{+} = (1,1,1)$ and $\tilde{v}_j^{-} = (0,0,0)$, j=1, 2,3,….n.

**Calculating separation distances of alternatives from the FPIS and the FNIS:** The separation distances of alternatives from the FPIS and the FNIS provides the measure of the closeness of the alternatives from the FPIS and the FNIS. In the literature, various methods are available to measure the separation distance between two fuzzy numbers such as the vertex method, geometric method, dissemblance index method and Bhattacharyya distance method (Zwick 1987). In this study, the vertex method has been adapted for its simplicity. The following equations provided separation distance of the two fuzzy numbers:

$$d(\tilde{v}_{ij}, \tilde{v}_j^{+}) = \sqrt{\frac{1}{3}\left[(\tilde{v}_{ija} - \tilde{v}_{ja}^{+})^2 + (\tilde{v}_{ijb} - \tilde{v}_{jb}^{+})^2 + (\tilde{v}_{ijc} - \tilde{v}_{jc}^{+})^2\right]} \quad [6.15]$$

$$d(\tilde{v}_{ij}, \tilde{v}_j^{+}) = \sqrt{\frac{1}{3}\left[(\tilde{v}_{ija} - \tilde{v}_{ja}^{+})^2 + (\tilde{v}_{ijb} - \tilde{v}_{jb}^{+})^2 + (\tilde{v}_{ijc} - \tilde{v}_{jc}^{+})^2\right]} \quad [6.16]$$

$$D_i^{+} = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^{+}), \quad i = 1, 2, 3, ....., m \quad [6.17]$$

$$D_i^{-} = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^{-}), \quad i = 1, 2, 3, ....., m \quad [6.18]$$

For the illustrative example, the separation distance ($D^{+}$ )of alternatives A1, A2, A3, and A4 from FPIS are 2.50, 1.95, 2.75, and 2.75, respectively and the separation distance ($D^{-}$ )of alternatives A1, A2, A3, and A4 from FNIS are 0.96, 1.84, 0.49, and 0.49, respectively.

**Step 8. Calculating relative closeness coefficient (CC):** The relative closeness coefficient of each alternative with respect to the FPIS ($A^{+}$) and FNIS ( $A^{-}$ ) is calculated as follows:

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad , \qquad i = 1, 2, 3, \ldots, m \qquad [6.19]$$

The calculated closeness coefficients (CCs) provide the distance measure of alternatives (the *"causes"*) from the FPIS and the FNIS. The values of CCs provide information for the impacts of WQF "*causes"* to the WQF "*symptoms"* in an exhaustive scale of [0, 1]. The value of a CC is the highest (maximum contribution to the WQF potential) when it reaches to the FPIS and the lowest to zero (minimum contribution to the WQF potential) when it reaches to the FNIS. Therefore, the lower values of CCs of all the *"causes"* indicate a better water quality. An increase of CC value of a WQF "*cause"* indicates the deterioration of water quality due to that particular WQF "*cause"*. In a WDS with normal values of CCs, a sudden increase of a CC of a WQF "*cause"* will help for the identification and detection of WQF.

For the illustrative example, the closeness coefficients (CCs) for alternatives, A1, A2, A3, and A4 are 0.28, 0.49, 0.15, and 0.15, respectively. Therefore, it is evident that the most influential parameter for the illustrative example is A2 (TOC).

**Step 9. Aggregating WQF potential:** In a MCDM problem, in many situations, strict '*and'* or *'or'* cannot explain the situation. To address the issue Yager (1988) introduced the ordered weighted averaging (OWA) operator as form of generalized mean type operator. The OWA operator provides flexibility to utilize the range of "*anding*" or *"oring"* which helps to include the decision maker's attitude in the aggregation process (Sadiq et al. 2010).

An OWA operator of dimension *n* is a mapping of $\phi : R^m \rightarrow R$ where R = [0, 1] which has associated to a set of weights or weighting vector, w =($w_1$, $w_2$... ,$w_m$) to it, so that $w_i \in [0, 1]$ and $\sum_{i=1}^{m} w_i = 1$ . Therefore for a given *m* factors ($a_1$, $a_2$..., $a_m$), the OWA aggregation is performed by following equation:

$$OWA(a_1, a_2, \ldots\ldots, a_m, = \sum_{i=1}^{m} w_i b_i \qquad [6.20]$$

where, $b_i$ is the $i^{th}$ largest element in the vector ($a_1$, $a_2$... ,$a_m$), and $b_1 \geq b_1 \geq \ldots\ldots \geq b_m$ . The weight $w_i$ is not associated with any particular value of $a_i$ rather it entirely depends on the ordinal position of $b_i$.

For evaluating WQF potential, the estimated values of CCs of the element of the vector ($a_1$, $a_2$... ,$a_m$) are considered. As none of the single CC can fully appreciate the overall WQF potential, their aggregated impacts will provide the overall WQF potential.

In the literature, different methods of OWA weight generation have been documented by different investigators. Yager (1988) first proposed a class of function called regularly increasing monotone (RIM) quantifier to generate OWA weights. The functions of this class are bounded by two linguistic quantifiers: "there exists", $Q^*(r)$ (or) and "for all", $Q_*(r)$ (and). Thus, the limit of RIM quantifier Q(r) is $Q_*(r) \le Q(r) \le Q^*(r)$ (Yager and Filev 1994). For a given RIM quantifier, the OWA weights can be generated as follows:

$$w_i = \left(\frac{i}{m}\right)^{\delta} - \left(\frac{i-1}{m}\right)^{\delta}, \quad i = 1,2\cdots,m \qquad [6.21]$$

where, δ is a degree of a polynomial function. For δ=1, the function becomes a uniform distribution (i.e., $w_i = 1/m$). For δ>1, the RIM function becomes "*and-type*" operator (a conjunctive operator or a t-norm) manifesting negatively skewed OWA weight distribution. For δ<1, the RIM function becomes "*or-type*" operator (a disjunctive operator or an s-norm) manifesting positively skewed OWA weight distribution. Yager (1998) defined the range between the two extremes through the concepts of *orness* (α) function as follows:

$$\alpha = \frac{1}{m-1}\sum_{i=1}^{m} w_i (m-i) \quad \text{and } \alpha \in [0,1]. \qquad [6.22]$$

The function orness express the degree to which the aggregation is like an '*or'* operator. An α=0 represents the minimum value in the multi-criteria vectors having weight vector w=(0,0,0,…,1) and an α=1 represents the reverse, i.e., the maximum value in the multi-criteria vector. In addition, if all the elements in the multiple criteria vectors are assigned equal weight (e.g., w=1/m,1/m,…,1/m), the orness becomes α=0.5, It is noted that α=0.5 does not guarantee the uniform distribution of weight rather guarantees a symmetry only on both side of the median ordinal position.

For the illustrative example, although 4 *"causes"* have been identified, water can be undrinkable even only for one "*cause"*. Therefore, the aggregation of CCs has been carried out using an *or-type* operator. For this study, various values of δ have been investigated. Finally, based on engineering judgment, a value of δ=0.2 which as the estimated value of *orness* (α) is 0.86, has been selected. The value of α=0.86 which is between [0.5, 1] ensures the *or-type* influence to the aggregation process.

## 6.3 Full Scale Model Development and Application

According to the methodology presented in Section 6.2, a full scale model has been developed considering all the possible *causes* and *symptoms*. For this model, 17 *causes* and nine *symptoms* have been identified. Table 6.8 provides a summary description of the identified *"causes"* and *"symptoms"* for a full scale model.

Table 6.8: Summary description of the *causes* and the *symptoms* for the WQF

| Parameters | Descriptions | References |
|---|---|---|
| ***Causes*** | | |
| Water temperature | In normal condition, water temperature has no significant impact on human body. However, in extreme conditions, it may be very toxic to the human body. Besides own toxic effects, it changes solubility of many water quality parameters. With increase in temperature, water loses capacity to hold dissolve oxygen. It also influences the formation of microbial community in biofilm, organic contents, and chorine demand. There is no special guideline for drinking water temperature, however, human being prefers cooler water (~15-21 $^0$C) compared to warm water. | Sandick et al. 1984<br>Moll et al. 1999 |
| Water pressure | Contaminant intrusion is one of the primary reasons of post treatment water quality failure in WDS. Low pressure or pressure drop is one of the most reasons for the post treatment contaminant intrusion in WDS. To prevent contaminant intrusion in WDS, the internal pressure of a pipe always must be higher than the outside pressure. | Sadiq et al. 2006 |
| Water velocity | Velocity of water affects the biofilm formation. Age of water in water distribution system will increase with decreasing water velocity. Usually WDSs are designed to maintained velocities in the pipe in the range of 0.5 to 1.5 m/s. However, it also could goes up to 3 or 4 m/s. | Soini et al. 2002<br>Simpson and Elhay 2008 |
| Free residual chlorine | Free residual chlorine in water is the chlorine concentration available for disinfection to inactivate the disease-causing organisms. According to WHO (2008), at the point of delivery, the minimum residual free chlorine concentration should be 0.2 mg/litre. However, for effective disinfection, residual free chlorine concentration should be more or equal to 0.5mg/litre after at least 30 min contact time at pH <8.0. It also plays an important role in aesthetic and taste of drinking water. | WHO 2008 |
| Lead | The most common sources of lead in drinking water are pipes, joints, fixtures and faucets (brass) and fittings. Due to its severe toxicity, a small dose of lead | US EPA 2011a |

| | | |
|---|---|---|
| | may cause different health problem including behavioral problem and learning disabilities. Children under the age of six are the most vulnerable. However, a long exposure of lead of adults may cause kidney problem and high blood pressure. US EPA maximum contaminant level goal (MCLG) for lead is zero and action level 10ppb. | |
| Copper | Copper is very common chemical available in the atmosphere. However, concentration in drinking water is relatively higher than natural environment due to various pipe materials and associated reaction. Copper concentration in drinking water varies with pH, hardness, dissolve oxygen, presence of different oxidizing agents, pipe materials, and chelating compounds or ions. Studies in North America and Europe show that the copper concentration in drinking water is ranged from ≤0.005 to>30mg/l. In USA, drinking guideline for copper is 1.3mg/l. | Health Canada 1992; IPCS 1998; US EPA 1991; 1995; 2011b; US NRC 2000; WHO 2004 |
| Total organic carbon | Total organic carbon (TOC) is an indirect measure of organic carbon in water. It provides important information on formation DBPs and microbial contamination. During the disinfection process, in certain condition, disinfectants react with the natural organic matter in water and produces a certain types byproducts which could be potential carcinogenic or pose other harmful health effects. According to the US EPA (2002), recommended TOC levels in source water and treated water are less than 2 mg/l and 1 mg/l, respectively. UV254mn can be used as a surrogate for the measure of TOC. | US EPA 2002; Wallace et al. 2002 |
| Chloride | Almost all natural water contains chloride in the form of salt of sodium chloride (NaCl), potassium chloride (KCl) and Calcium chloride ($Ca_2Cl$). Excess chloride concentration creates undesirable water characteristic including increased electrical conductivity and pipe corrosions. Recommended chloride concentration of drinking water range from 10mg/l to 100mg/l. A chloride concentration more than 250mg/l can leads to detectable taste in drinking water. | Gregory 1990; WHO 1978; 1996a |
| Nitrite and Nitrate | The source water linked with agricultural land, waste disposal land, wastewater and polluted groundwater is the most important source of nitrite and nitrate in drinking water. Nitrate is associated with methaemoglobinaemia or blue baby diseases for infants. According to WHO (2008) guideline, values for short term exposure of Nitrite (as $NO_2^-$) and Nitrate (as $NO_3^-$) are 3 mg/litres and 50 mg/litres, respectively. However, for long term exposure is much less to 0.2[19] mg/litres. | WHO 2008 |
| Phosphorous | A certain amount of phosphorous is desired in drinking water. Addition of phosphorous in drinking water increases the microbial growth of water irrespective of sources of water up to a phosphate concentration of 10 mg/l of $PO4^-$ P. | Fang et al. 2009; Fang et al. 2010; Miettinen et al. 1997 |
| Ammonia | Presence of ammonia in drinking water does not have immediate effect on human health. A concentration higher than natural level (0.2 mg/l) is an indicator of faecal pollution. Taste, odor increased and disinfection efficiency decreased if drinking water contains more than 0.2mg/l of ammonia is chlorinated. Cement mortar used for coating insides of water pipes may release considerable amounts of ammonia into drinking water and compromise disinfection with chlorine. | WHO 1986; 1996b |
| Turbidity | Turbidity is a measure of the suspended solids and colloidal matter. Turbidity is negatively correlated with disinfection efficiency and interferes with maintenance of free chlorine residual. WHO Guidelines for median turbidity is | Eaton and Franson 2005; LeChevallier |

[19] Provisional guideline value, as there is evidence of a hazard, but the available information on health effects is Limited (WHO, 2008)

| | | |
|---|---|---|
| | below 0.1 NTU for effective disinfection. According to Health Canada, all time treated water turbidity target is less than 0.1NTU | et al. 1981<br>Health Canada 2003 |
| Pipe materials and Age | Pipe material and age can have impact on corrosion, leaching, number of leaks and breaks and the formation of biofilm. Internal corrosion of aged metal pipes may increase the concentration of metal compounds in the water. Metals may leach into water, causing taste and odour problems. Large quantities of metal pipes may lead to WQF. | Kleiner 1998 |
| Water pH | The pH affects the chemistry of water and disinfection efficiency. Low pH water can increase corrosion rates in metal pipes. At pH 6, 96.5% of the free residual chlorine is available in the form of HOCl whereas at pH8.5, only 10% is available. Microbial changes and releases into the water can be triggered by rapid or extensive pH fluctuations. The recommended pH for drinking water is 6.5 to 7.5. | Payment et al. 2003; Sadiq et al. 2007 |
| TTHMs (Total trihalomethanes) | THMs make up one of the major groups of disinfection by-products formed during a reaction between disinfectant and natural organic matter contained in water under suitable conditions. THMs are toxic and may increase the risk of bladder cancer in cases of long-term exposure. TTHMs include chloroform, dichlorobromomethane, dibromochlorometane and bromoform. The USEPA established maximum contaminant level (MCL) is 80 µg/L. | US EPA, 1998 |
| ***Symptoms*** | | |
| Water color | Color in drinking water is linked with the aesthetic. Drinking water should be colorless, however, in some cases drinking water becomes brown, red, orange, or yellow, usually caused by rust resulting from corrosion. Presence of color indicates the presence of dissolved solids which also reduces the disinfection efficiency. | |
| Odor | Although odor problem in drinking water is rare. Odor in the drinking water indicates presence high degree of undesirable material. A mild odor can also cause by excessive chlorination, temperature change. | |
| Taste | The common reasons for undesirable tastes of drinking water are the presence of excessive free residual chlorine, high temperature, presence of dissolve, and suspended solids. | |
| Reported waterborne disease | Generally, the number of reported waterborne disease increases with decrease in microbial quality of water. | |
| Presence of chemicals | Presence of different chemicals (such as lead, cupper etc.) will be considered as *symptoms* of water quality failure due to chemical contamination. | |
| Heterotrophic plate count | Heterotrophs are microorganisms including bacteria, moulds, yeasts that require organic carbon for their growth. An increase in HPC numbers indicates, in some cases, treatment breakthrough, post-treatment contamination or growth in the water or the presence of deposits and biofilm in the WDS. A sudden increase in HPC above historic baseline values should trigger actions to investigate and, if necessary, remediate the situation. | Francisque *et al.* 2009a,<br>Sartory 2004<br>Kirmeyer *et al.* 2000<br>WHO 2004 |
| Oxidation reduction potential (ORP) | ORP is a measure of changes in oxidizer level in water and measured in mVolt. It is the difference of concentration of oxidants and the reductants in the water. To deal with contaminates, which normally reductants, ORP should be more than zero. WHO recommended ORP for drinking water is 650 millivolts to destroy harmful organisms almost instantaneously. | |
| Dissolve oxygen | Dissolve oxygen (DO) is a measure of healthy water. DO changes with the increased temperature and presence of bacteria. The level of DO has effect on color, odor and taste. However, higher level of DO speed up the corrosion in water pipe. | |

| | |
|---|---|
| Specific conductivity | Specific conductance measures the electrical conductivity of water and gives an idea of presence of dissolve solids such as salt in the water. A high level of dissolve solids may create an unpleasant taste and odor or it may even create gastrointestinal distress. |

The same committee members, who were consulted for the simplified example, established the causal relationship (Figure 6.3) among different WQF *causes* (alternatives) and *symptoms* (criteria) for the full scale model.

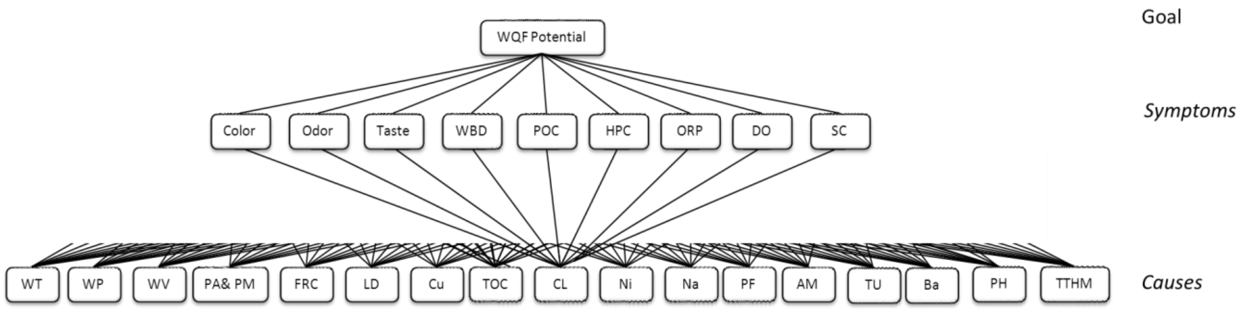



Figure 6.3: Interrelation of different criteria (*symptoms*) and alternatives (*causes*)

WBD= Waterborne diseases ; POC= Presence of chemicals; HPC= heterotrophic plate count; ORP: Oxidation-reduction potential; DO= Dissolve oxygen; SC= Specific conductivity; WT=Water temperature ($^oC$); WP=System pressure(m); WV=Water velocity in pipe (m/s); PA= Pipe age (year); PM=Pipe materials; FRC=Free residual chlorine (mg/l); LD=Lead (mg/l); Cu=Copper (mg/l); TOC=Total organic carbon (mg/l); CL=Chloride (mg/l); Ni=Nitrite (mg/l); Na=Nitrate (mg/l); PF=Phosphorous (mg/l); AM=Ammonia (mg/l); TU= Turbidity (NTU); Ba= Total coliforms (no.); PH=pH; TTHM= Total tri-halomethane

Similar to the illustrative example, a dynamic system of experts' opinion has been created containing expert opinion for the rating of the alternatives for all possible values for the alternatives. To support the experts, a list of recommended values of different parameters was provided to them. Table 6.9 shows the list of WQF "*causes"* and *"symptoms"* and their recommended values for a WDS. Based on the causal relationship and expert opinion, a Fuzzy-TOPSIS-OWA-based full scale WQF potential model has been developed.

To evaluate the practicality of this research, the developed full scale model has been implemented in a WDS serving nearly 240,000 people in Quebec City (Canada). At the time of data collection, the Quebec City WDS is feed with surface water from the Saint-Charles River which passes the treatment plant through a process of pre-chlorination followed by coagulation-flocculation-sedimentation, slow sand filtration, ozonation and post-chlorination (Rodriguez et al. 2007).

Table 6.9: Recommended values of the *causes* and the *symptoms*

| | *Causes* of WQF | | | *Symptoms* of WQF | |
|---|---|---|---|---|---|
| SL No. | Name | Symbol | Guideline values | Name | Guideline values |
| 1 | Water temperature ($^0$C) | WT | 15-21 | Color, TCU | 15 |
| 2 | System pressure, m | SP | 40 | Odor | - |
| 3 | Water velocity in pipe, m/s | WV | >0.5 | Taste | - |
| 4 | Pipe age[20], yr | PA | <30 | Reported waterborne disease, no | 0 |
| 5 | Free residual chlorine, mg/l | FRC | 0.2-0.5 | Presence of chemicals | - |
| 6 | Lead, ppb | LD | 10 | Heterotrophic plate count, CFU | 100 |
| 7 | Copper, mg/l | Cu | 1.3 | Oxidation-reduction potential, mV | 650 |
| 8 | Total organic carbon, mg/l | TOC | <1 | Dissolve oxygen, mg/l | 2 |
| 9 | Chloride, mg/l | CLD | 10 | Specific conductivity, µS/m | |
| 10 | Nitrite (as $NO_2^-$),mg/l | NI | 3 | | |
| 11 | Nitrate(as $NO_3^-$), mg/l | NA | 50 | | |
| 12 | Phosphorous, mg/l | PH | 10 | | |
| 13 | Ammonia, mg/l | AM | 0.2 | | |
| 14 | Turbidity, NTU | TU | 0.1 | | |
| 15 | Total coliforms, no. | Ba | 0 | | |
| 16 | pH | PH | 6.5-7.5 | | |
| 17 | TTHM, µg/l | THM | 80 | | |

Although the full scale model evaluates identified 17 *"causes"* against nine *"symptoms"*, data were only available for seven parameters. Considering limited relevance of the remaining parameters, their values were assumed which were lower than their regulatory requirements. For the data collection, intensive sampling campaign has been carried out in several locations during years 2003, 2004 and 2005. All samples were collected in commercial and public buildings after flushing water for about 5 minutes. In most cases, locations were sampled every two weeks.

Samples have been collected[21] for water temperature, pH, turbidity, coliforms, free residual chlorine, and ultraviolet absorbance at 254 nm (UV-254 nm). All the parameters were measured in the Quebec City water quality laboratory except the water temperature and free residual chlorine which were measured in the field. Samples were transported to the laboratory in iceboxes to maintain their temperature at 4$^o$C.

[20] As the pipe age and material are considered as a single alternative ("cause") in WQF potential evaluation. Decision makers need to consider pipe material when they are evaluating pipe age and vice versa.

[21] For this study, it is assumed that all the data are readily available. The uncertainties in data collection, data processing and data compilation have not been considered.

Table 6.10: Data used for the modelling of WQF potential for the study area

| Parameters | WT | | PH | | TTHM | | FRC | | TU | | UV-254 | | Age | | Pipe Materials (%) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| NO_POINT | Mean | STD | Mean | STD | Mean | STD | Mean | STD | Mean | STD | Mean | STD | Mean | STD | Metal | Non-metal |
| QC202 | 11.45 | 6.21 | 7.45 | 0.19 | 49.56 | 18.26 | 0.19 | 0.19 | 0.36 | 0.21 | 3.24 | 0.56 | 59.04 | 13.00 | 75% | 25.00% |
| QC207 | 11.18 | 4.48 | 7.45 | 0.21 | 59.16 | 40.68 | 0.18 | 0.13 | 0.34 | 0.09 | 3.16 | 0.39 | 66.21 | 32.52 | 33% | 66.67% |
| QC201 | 10.10 | 7.56 | 7.46 | 0.19 | 23.61 | 12.31 | 0.82 | 0.15 | 0.28 | 0.14 | 2.37 | 0.41 | 89.57 | 41.95 | 69% | 30.77% |
| QC101 | 11.25 | 6.91 | 7.55 | 0.20 | 22.53 | 16.49 | 0.70 | 0.19 | 0.29 | 0.15 | 2.53 | 0.50 | 91.73 | 30.10 | 84% | 15.63% |
| QC204 | 11.06 | 7.76 | 7.42 | 0.27 | 54.89 | 48.72 | 0.88 | 0.22 | 0.27 | 0.12 | 2.40 | 0.41 | 71.04 | 23.08 | 100% | 0.00% |
| QC105 | 10.14 | 6.67 | 7.56 | 0.20 | 40.94 | 22.94 | 0.40 | 0.19 | 0.36 | 0.29 | 2.67 | 0.48 | 62.66 | 15.40 | 88% | 11.76% |
| QC114 | 13.21 | 3.02 | 7.46 | 0.21 | 41.94 | 22.09 | 0.14 | 0.13 | 0.42 | 0.48 | 3.01 | 0.45 | 62.05 | 27.65 | 75% | 25.00% |
| QC111 | 9.19 | 6.21 | 7.53 | 0.27 | 42.63 | 27.87 | 0.32 | 0.19 | 0.31 | 0.12 | 2.51 | 0.50 | 53.78 | 26.86 | 88% | 12.50% |
| QC109 | 10.56 | 5.88 | 7.65 | 0.31 | 65.42 | 17.76 | 0.24 | 0.31 | 0.53 | 0.50 | 3.35 | 1.17 | 47.67 | 16.74 | 100% | 0.00% |
| QC107 | 11.38 | 5.44 | 7.62 | 0.20 | 33.38 | 24.13 | 0.44 | 0.31 | 0.44 | 0.51 | 2.78 | 0.58 | 67.17 | 43.46 | 100% | 0.00% |
| QC116 | 12.55 | 4.34 | 7.47 | 0.17 | 43.54 | 24.02 | 0.05 | 0.08 | 0.37 | 0.21 | 2.86 | 0.46 | 46.85 | 17.54 | 94% | 5.56% |
| QC117 | 10.10 | 3.75 | 8.26 | 0.70 | 50.63 | 24.66 | 0.02 | 0.04 | 1.11 | 0.92 | 3.86 | 1.53 | 64.37 | 20.62 | 82% | 17.65% |
| QC119 | 11.44 | 5.50 | 7.48 | 0.17 | 32.62 | 17.84 | 0.16 | 0.15 | 0.53 | 0.69 | 3.06 | 1.04 | 64.37 | 20.62 | 82% | 17.65% |
| QC118 | 11.06 | 7.06 | 7.52 | 0.20 | 37.28 | 26.58 | 0.58 | 0.11 | 0.37 | 0.15 | 2.52 | 0.30 | 64.36 | 22.31 | 100% | 0.00% |
| QC327 | 11.17 | 5.89 | 7.48 | 0.26 | 37.02 | 25.91 | 0.14 | 0.11 | 0.29 | 0.12 | 2.63 | 0.60 | 42.52 | 20.52 | 87% | 13.11% |
| QC113 | 11.29 | 6.27 | 7.49 | 0.19 | 41.25 | 24.36 | 0.31 | 0.20 | 0.38 | 0.19 | 2.94 | 0.73 | 96.17 | 29.20 | 92% | 8.11% |
| QC309 | 12.03 | 5.40 | 7.52 | 0.23 | 42.46 | 18.79 | 0.71 | 0.20 | 0.28 | 0.26 | 2.48 | 0.60 | 37.67 | 17.82 | 88% | 11.54% |
| QC326 | 15.50 | 5.00 | 7.48 | 0.23 | 38.22 | 21.80 | 0.27 | 0.09 | 0.19 | 0.07 | 2.57 | 0.66 | 37.67 | 17.82 | 88% | 11.54% |
| QC308 | 10.89 | 6.80 | 7.51 | 0.24 | 36.10 | 27.03 | 0.54 | 0.20 | 0.32 | 0.15 | 2.72 | 0.59 | 44.73 | 6.09 | 60% | 40.00% |
| QC320 | 10.14 | 7.55 | 7.53 | 0.19 | 39.52 | 27.39 | 0.66 | 0.14 | 0.36 | 0.13 | 2.63 | 0.31 | 71.77 | 21.31 | 36% | 64.29% |
| QC206 | 10.23 | 5.36 | 7.53 | 0.20 | 44.95 | 26.14 | 0.09 | 0.10 | 0.31 | 0.19 | 3.05 | 0.44 | 47.81 | 9.83 | 100% | 0.00% |
| QC408 | 9.45 | 4.40 | 8.12 | 0.40 | 57.45 | 30.10 | 0.34 | 0.29 | 0.32 | 0.14 | 2.81 | 0.46 | 55.98* | 20.5* | 0% | 100.00% |
| QC412 | 11.57 | 5.56 | 7.56 | 0.23 | 38.58 | 25.07 | 0.64 | 0.21 | 0.26 | 0.15 | 2.54 | 0.42 | 55.98* | 20.5* | 10% | 89.66% |
| QC404 | 10.34 | 5.58 | 7.60 | 0.22 | 36.44 | 25.08 | 0.13 | 0.16 | 0.77 | 0.39 | 4.81 | 1.40 | 55.98* | 20.5* | 84% | 15.79% |
| QC402 | 9.01 | 7.19 | 7.69 | 0.25 | 58.76 | 0.00 | 0.76 | 0.21 | 0.30 | 0.41 | 2.32 | 0.59 | 55.98* | 20.5* | 100% | 0.00% |
| QC314 | 13.03 | 4.46 | 7.51 | 0.19 | 34.88 | 20.62 | 0.12 | 0.11 | 0.33 | 0.21 | 3.30 | 1.17 | 55.98* | 20.5* | 100% | 0.00% |

WT = Water temperature, TTHM = Total Trihalomethanes, FRC = Free residual chlorine , TU = Turbidity

| Parameters | WT | | PH | | TTHM | | FRC | | TU | | UV-254 | | Age | | Pipe Materials (%) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| NO_POINT | Mean | STD | Mean | STD | Mean | STD | Mean | STD | Mean | STD | Mean | STD | Mean | STD | Metal | Non-metal |
| QC407 | 9.89 | 6.71 | 7.81 | 0.35 | 39.59 | 25.72 | 0.96 | 0.28 | 0.25 | 0.24 | 2.40 | 0.70 | 55.98* | 20.5* | 100% | 0.00% |
| QC311 | 10.16 | 6.77 | 7.53 | 0.21 | 32.45 | 23.73 | 0.75 | 0.15 | 0.26 | 0.14 | 2.38 | 0.50 | 33.88 | 5.17 | 77% | 22.58% |
| QC316 | 11.15 | 6.28 | 7.53 | 0.28 | 26.73 | 16.05 | 0.48 | 0.17 | 0.22 | 0.11 | 2.50 | 0.51 | 55.98* | 20.5* | *66% | *33.68% |
| QC321 | 10.64 | 4.58 | 7.53 | 0.26 | 49.56 | 34.45 | 0.25 | 0.12 | 0.29 | 0.10 | 2.52 | 0.40 | 34.23 | 12.23 | 27% | 72.55% |
| QC322 | 11.21 | 4.72 | 7.48 | 0.23 | 41.34 | 16.22 | 0.08 | 0.09 | 0.21 | 0.08 | 2.33 | 0.39 | 34.23 | 12.23 | 27% | 72.55% |
| QC315 | 11.57 | 6.10 | 7.60 | 0.19 | 38.81 | 32.63 | 0.43 | 0.13 | 0.33 | 0.26 | 2.75 | 0.49 | 55.98* | 20.5* | *66% | *33.68% |
| QC324 | 10.63 | 4.79 | 7.70 | 0.23 | 53.82 | 32.03 | 0.13 | 0.09 | 0.26 | 0.14 | 2.51 | 0.33 | 36.61 | 13.06 | 60% | 39.73% |
| QC328 | 9.09 | 6.22 | 7.64 | 0.23 | 38.29 | 31.51 | 0.60 | 0.13 | 0.24 | 0.08 | 2.46 | 0.53 | 36.61 | 13.06 | 60% | 39.73% |
| QC304 | 11.36 | 6.75 | 7.53 | 0.22 | 31.47 | 23.01 | 0.79 | 0.18 | 0.24 | 0.13 | 2.47 | 0.64 | 46.66 | 19.21 | 71% | 29.03% |
| QC325 | 12.50 | 4.96 | 7.50 | 0.22 | 45.68 | 18.92 | 0.05 | 0.09 | 0.47 | 0.59 | 2.52 | 0.92 | 25.69 | 9.90 | 21% | 79.07% |
| QC302 | 11.80 | 5.85 | 7.58 | 0.21 | 25.64 | 14.87 | 0.68 | 0.11 | 0.26 | 0.17 | 2.62 | 1.24 | 55.98* | 20.5* | 46% | 53.76% |
| QC305 | 9.80 | 7.38 | 7.52 | 0.29 | 26.78 | 27.34 | 0.86 | 0.23 | 0.33 | 0.48 | 2.62 | 1.12 | 55.98* | 20.5* | 74% | 26.06% |
| QC413 | 11.76 | 4.60 | 7.50 | 0.20 | 39.47 | 21.20 | 0.20 | 0.15 | 0.46 | 0.35 | 3.08 | 0.72 | 55.98* | 20.5* | 57% | 43.43% |
| QC318 | 10.32 | 4.71 | 7.62 | 0.25 | 37.87 | 21.45 | 0.29 | 0.13 | 0.29 | 0.17 | 2.71 | 0.54 | 55.98* | 20.5* | 100% | 0.00% |
| QC317 | 11.25 | 6.00 | 7.50 | 0.22 | 34.65 | 24.01 | 0.37 | 0.17 | 0.49 | 0.26 | 3.32 | 0.96 | 55.98* | 20.5* | 27% | 72.53% |
| QC329 | 10.27 | 5.05 | 7.61 | 0.23 | 41.39 | 36.54 | 0.25 | 0.20 | 0.59 | 0.85 | 3.03 | 0.59 | 55.98* | 20.5* | 22% | 77.60% |
| QC330 | 12.36 | 3.17 | 9.38 | 0.19 | 55.60 | 17.00 | 0.03 | 0.05 | 0.35 | 0.19 | 2.96 | 0.55 | 55.98* | 20.5* | 22% | 77.60% |
| QC323 | 10.36 | 7.30 | 7.59 | 0.18 | 25.49 | 14.53 | 0.36 | 0.13 | 0.26 | 0.15 | 2.66 | 0.24 | 44.26 | 6.37 | 39% | 60.68% |
| QC301 | 11.08 | 5.97 | 7.65 | 0.21 | 36.26 | 25.94 | 0.48 | 0.13 | 0.24 | 0.12 | 2.46 | 0.48 | 55.98* | 20.5* | 0% | 100.00% |
| QC205 | 10.37 | 6.41 | 7.55 | 0.16 | 42.32 | 25.35 | 0.31 | 0.16 | 0.33 | 0.13 | 2.67 | 0.47 | 56.95 | 15.51 | 72% | 28.00% |
| QC319 | 11.03 | 6.02 | 7.47 | 0.20 | 39.86 | 24.58 | 0.26 | 0.19 | 0.26 | 0.23 | 2.61 | 0.56 | 41.60 | 13.10 | 57% | 43.02% |
| QC110 | 9.20 | 5.53 | 7.54 | 0.16 | 29.89 | 18.52 | 0.25 | 0.21 | 0.36 | 0.23 | 2.93 | 0.77 | 64.03 | 22.07 | 77% | 23.08% |
| QC115 | 13.16 | 6.83 | 7.54 | 0.20 | 43.53 | 30.72 | 0.53 | 0.14 | 0.36 | 0.14 | 2.93 | 1.88 | 67.88 | 19.82 | 70% | 30.30% |
| QC102 | 9.86 | 7.49 | 7.54 | 0.22 | 23.06 | 8.76 | 0.42 | 0.18 | 0.31 | 0.13 | 2.56 | 0.54 | 73.36 | 46.60 | 69% | 30.77% |
| QC203 | 11.53 | 6.82 | 7.39 | 0.21 | 45.58 | 21.54 | 0.61 | 0.20 | 0.30 | 0.14 | 2.51 | 0.42 | 73.98 | 33.92 | 74% | 26.32% |
| Overall | 10.99 | 5.84 | 7.60 | 0.23 | 40.12 | 23.57 | 0.40 | 0.16 | 0.35 | 0.25 | 2.77 | 0.65 | 55.98 | 20.48 | 66.32% | 33.68% |

WT = Water temperature, TTHM = Total Trihlomethanes, FRC =Free residual chlorine , TU=Turbidity

* Missing of data and taken as average of available data

UV-254 nm was measured as an organic matter in water which was converted to total organic carbon (TOC) according to the equation developed by APHA (1999). For sampling of microbiological parameters, bottles were sterilized with sodium thiosulfate. Concentration of lead was monitored in few occasions in few zones. Average monitored lead concentration (0.5 ppb) in few zones has been used for all the zones. Detail of sampling and related data analysis has been reported in Francisque et al. (2009a,b). In addition to the water quality data, pipe age and their materials data have also been collected. Pipe materials are grouped as metal and non-metal. Table 6.10 shows collected data used for the case study.

Table 6.11: Data used for overall WQF potential evaluation

| SL No. | Name | Symbol | Modelled Mean | Source |
|---|---|---|---|---|
| 1 | Water temperature ($^0$C) | WT | 11 | MD |
| 2 | System pressure (m) | SP | 40 | AD |
| 3 | Water velocity in pipe (m/s) | WV | 0.17 | PC |
| 4 | Pipe age (yr) | PA | 55.97 | MD |
| 5 | Free residual chlorine (mg/l) | FRC | 0.40 | MD |
| 6 | Lead (ppb) | LD | 5 | MD* |
| 7 | Copper (mg/l) | Cu | 1 | AD |
| 8 | Total organic carbon (mg/l) | TOC | 1.39 | MD |
| 9 | Chloride (mg/l) | CLD | 5 | AD |
| 10 | Nitrite (as $NO_2^-$) (mg/l) | NI | 1 | AD |
| 11 | Nitrate(as $NO_3^-$), mg/l | NA | 13 | AD |
| 12 | Phosphorous, mg/l | PH | 5 | AD |
| 13 | Ammonia, mg/l | AM | 0.1 | AD |
| 14 | Turbidity, NTU | TU | 0.35 | MD |
| 15 | Total coliforms, no | Ba | 0 | AD |
| 16 | pH | pH | 7.6 | MD |
| 17 | TTHM, µg/l | THM | 40.1 | MD |

MD= Monitored data; MD*= Monitored data but available only for few locations; PC= Personal communication with the Director, Division of Water Quality, Environment Service, Quebec City; AD=Assumed data

Two scenarios have been investigated. In the first scenario, spatial distribution of WQF potential has been investigated. For the second scenario, overall WQF potential has been estimated using the average (over full WDS) water quality parameters. Table 6.11 shows the data used for overall WQF potential. To evaluate the sensitivity of the different parameters, Monte Carlo Simulations have been carried out followed by the estimation of spearman rank coefficients.

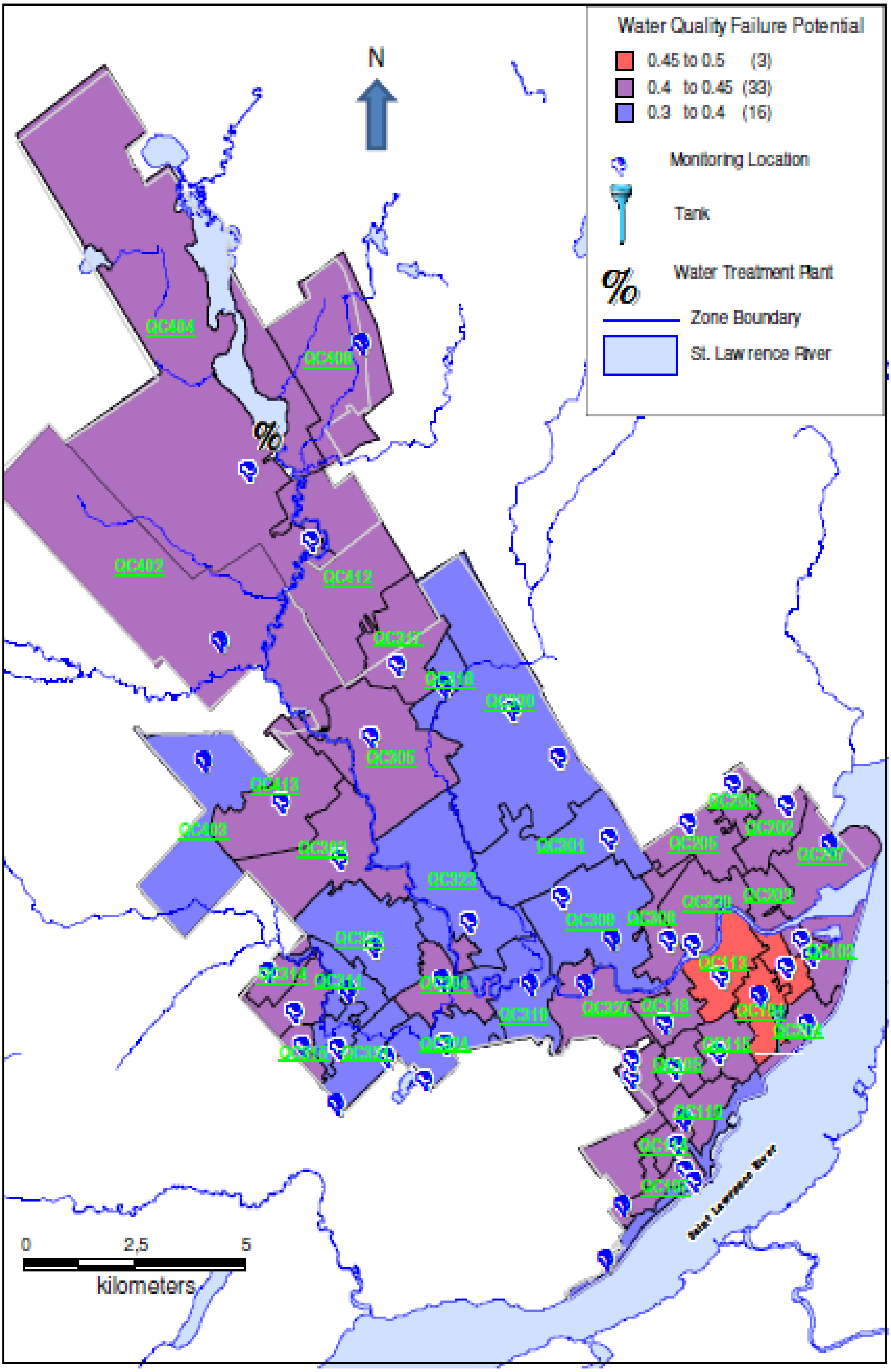



Figure 6.4: WQF potential in different zones of Quebec City WDS

## 6.4 Results and Discussion

Using Table 6.10 and assumed data shown in Table 6.11, the WQF potential has been estimated for different zones of the Quebec City WDS. Although each point data represents the sample location, here, each sample point represent a zone. Figure 6.4 shows the WQF potentials for different zones.

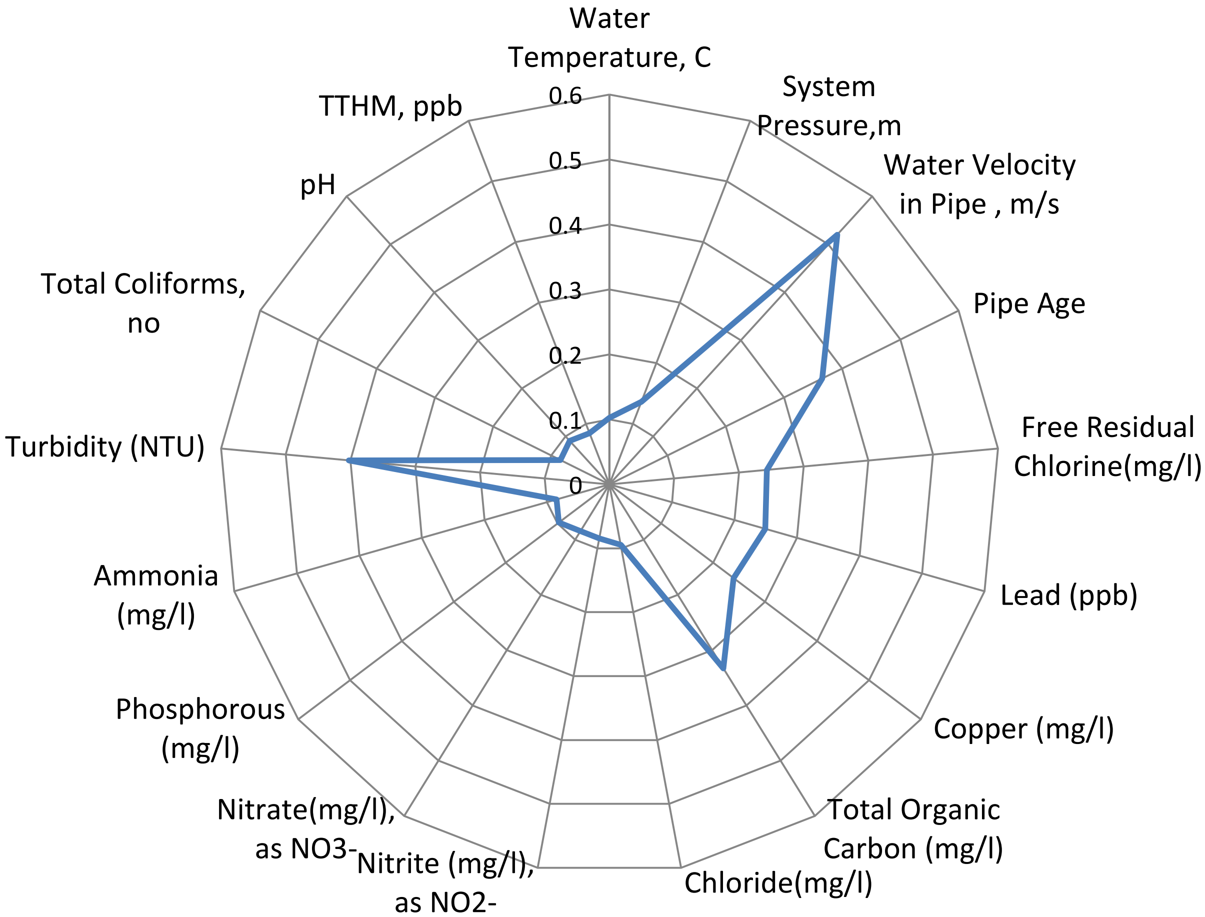



Figure 6.5: Comparative influences of different *causes* to the WQF potential

Figure 6.4 shows that out of 52 zones, 33 zones have the WQF potential between 40-45%, 16 zones have a WQF potential lower than 40% and only three zones have WQF potential higher than 45%. The estimated highest value of WQF potential is 50%. The variation of the WQF potentials is limited because the values of WQF "*causes*" are within the range of acceptable limits. In addition, data were available only for seven parameters and remaining 10 parameters values are assumed less than the guideline values.

To understand the effects of different *"causes"* to WQF potential, CCs are evaluated using average values of different parameters (*"causes"*) for all the zones. Figure 6.5 shows the web diagram of the different CCs.

For the current operating condition, Figure 6.5 shows that the low water velocity is the most important *"cause"* for higher WQF potential. The other influential parameters are turbidity, pipe age and material, total organic carbon, free residual chlorine, and lead. Low water velocity increases the water age and makes favorable environment for bacterial growth which is accelerated with higher pipe age (more biofilm) and lower free residual chlorine. The impacts of other parameters are minimal as their assumed values are in the range of recommended values. Only one data on water velocity has been obtained by personal communication which apparently might not the real spatial velocity distribution. To see the impacts of other parameters sensitivity analysis of the parameters has been carried out.

Uncertainties are inherently present in different WQF parameters (both in the *"causes"* and in the *"symptoms"*). To evaluate the impacts of different uncertain parameters to WQF potential, Monte Carlo (MC) simulation, programmed in standard MATLAB coding environment, has been conducted, while the Spearman rank correlation coefficients has been used to compare the impacts of different influencing parameters.

For MC simulations, all the identified 17 "*causes*" have been studied by assigning a probability distribution. For simplicity, a normal distribution for all "*causes*" of WQF has been used. In case of available data, the means were taken as study area average and in case of data lack, the means were assumed to values lower than the recommended values (Table 6.11). Standard deviations for each parameter has been assumed as 25% of the mean as assumed for demand multipliers by Torres et al. (2009).

MC simulations generate multiple trial input values to estimate the values of random outputs. It also predicts the error in the analysis which is inversely proportional to the number of iterations. According to ProjectSmart (2010), total error in MC simulation can be estimated as follows:

$$\varepsilon = \frac{3\sigma}{\sqrt{T}} \qquad [6.23]$$

where, $\sigma$ is the standard deviation and $T$ is the total number of iterations. This equation has been used to estimate the number of iterations for each MC simulation for a fixed value of $\varepsilon$ .

Considering $\varepsilon$ = 1.5% error, the total number of trials has been calculated for all the 17 variables. The estimated maximum number of trials is 1,200. However, as a conservative approach, in this study, 1,500 iterations were carried out. Furthermore to compare parameter-wise influence to WQF potential, Spearman rank correlation coefficients were estimated. If $u_t$ are the trial values of any input parameter and $v_t$ are the corresponding WQF potential values for those trial, then the Spearman rank correlation coefficients can be calculated by using Equation 6.24 (Walpole et al. 2007):

$$r_s = 1 - \frac{6}{T(T^2-1)} \sum_{t=1}^{T} d_t^2 \qquad [6.24]$$

where $t$ =1, 2, 3 ... $T$; $T$ is the number of pairs of data (number of iterations) and $d_t$ is the difference between the ranks of the $t^{th}$ value ($u_t$) of input parameter and the corresponding WQF potential value ($v_t$).

Figure 6.6 presents the resulting probability distribution function (PDF) and cumulative distribution function (CDF). Figure 6.6 shows that the WQF potential is quite sensitive to the WQF "*causes*" and the peak of PDF is around 42% representing the most of the iterations calculated WQF potential around 42%.

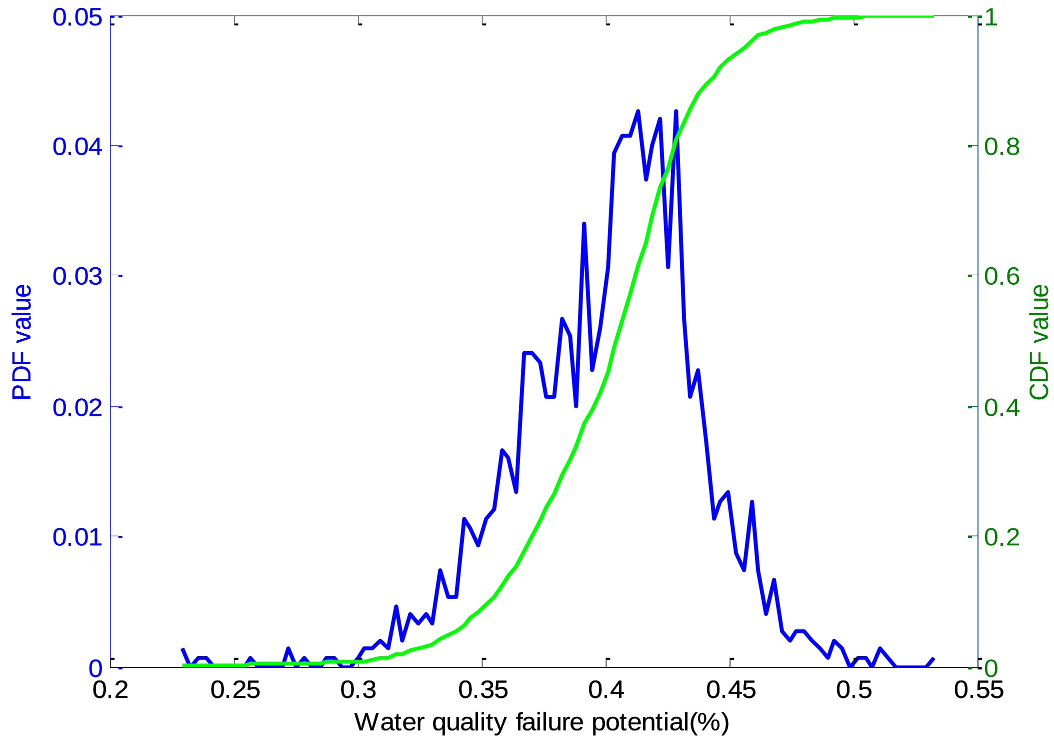



Figure 6.6: MC simulation results

For the developed model, the presence of coliforms is considered as a full failure of water quality. Therefore, the parameter coliform is the most influential parameter. To avoid the influences of coliform, the Spearman rank coefficients have been estimated excluding this parameter. Figure 6.7 shows the percentage contributions of different WQF "*causes*" to the WQF potential.

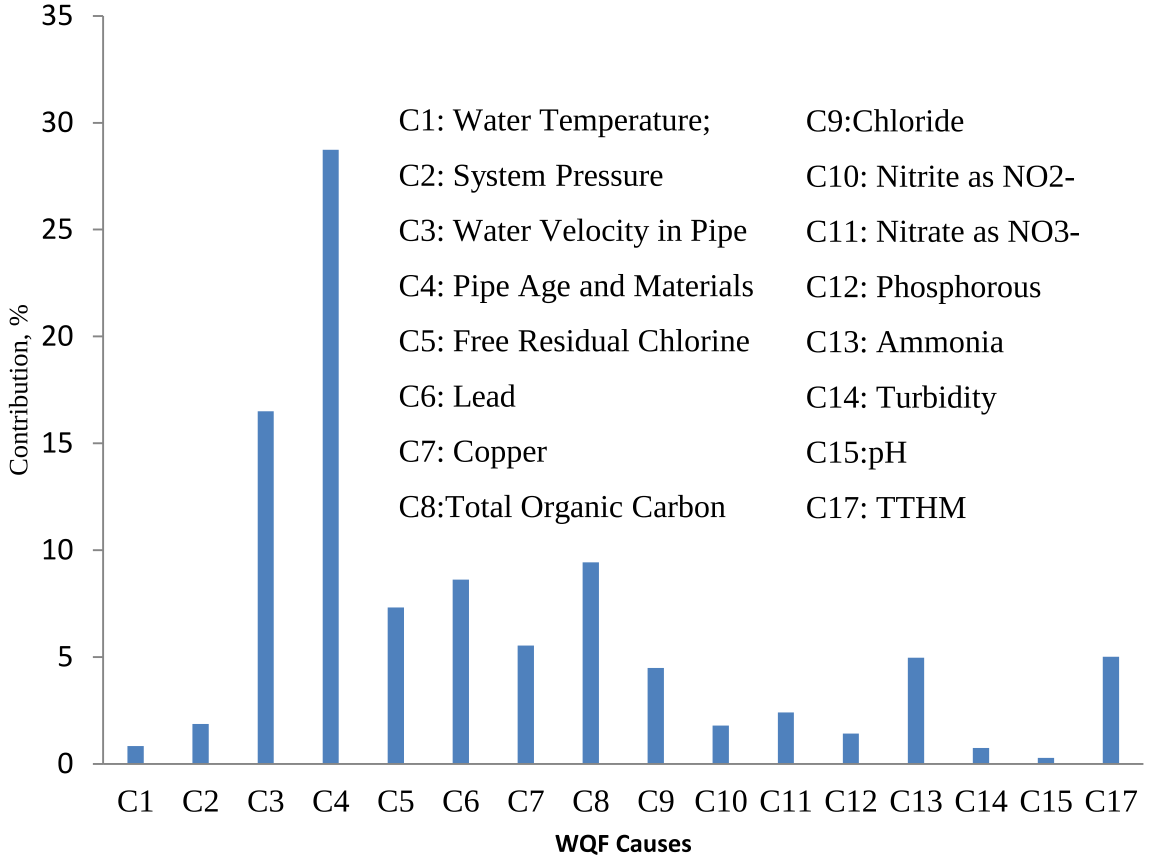



Figure 6.7: MC simulation results: percent contribution of WQF *causes*

Figure 6.7 shows that the pipe age and material is the most sensitive parameter. The more the pipes are elderly and the more there exist of metallic pipes, greater is the WQF potential. The next sensitive parameters are water velocity, total organic carbon, lead and total trihalomethane (TTHM). In fact, the parameters with values closer to the desirable values are less sensitive than the parameters with values closer to the undesirable values. Because a parameter value less than its regulatory requirement, is less sensitive in experts' ratings. The pH is the least sensitive "*cause*" of WQF as the pH is very close to the most desirable level. Percentage contributions of different WQF "*causes"* have been shown without signs because their non-monotonic nature of influence to the WQF potential. For example, presence of free residual chlorine is good only in certain range of its concentration. Presence of free residual chlorine less than certain threshold increases the risk of bacterial regrowth, and again, the presence of free residual chlorine more than a certain threshold increases the risk of disinfection by-products (DBP) formation.

## 6.5 Summary

This research has developed a fuzzy-TOPSIS-OWA-based model to evaluate the WQF potential for a water distribution system (WDS) based on various interacting *"causes"* and *"symptoms"*. The model has a capacity to evaluate WQF potential and identify the most probable reasons for water quality deterioration, considering complex physiochemical and microbial *cause-effect* relationship incorporating human judgments.

The developed model has been applied to a WDS in Quebec City with measured data for seven parameters out of 17 parameters. Some of the data have been estimated based on the information collected from the state-of-the-practice, manuals and the experience in the study area. From the sensitivity analysis, as expected, it appears that the presence of coliforms is the most influential parameter for the WQF potential. The next influential parameters are pipe age and material, water velocity, total organic carbon, lead, and total trihalomethane. The study also reveals that the pH is the least sensitive parameter.

For the current model, three decision makers participated in the evaluation process. However, the inclusion of additional decision makers' inputs might increase the model reliability. Like almost all of the risk-based modelling approaches, this model is difficult to validate. In spite of its limitations, the developed model can help water utility managers to identify the WQF potential. The identification of the WQF potential will guide utility managers to conduct better day-to-day operation, prioritization, and rehabilitation policy through better understanding of their network. The developed model can be extended for other cases for the similar problem.

In future, the developed model will be used to detect and diagnose the failure of water quality in a WDS. The model will be integrated with the US EPA developed EPANET (Rossman 2000) and EPANET-MSX (Shang et al. 2007) to develop a diagnosis tool that will give capability to detect and diagnosis the WQF in near real time.

# CHAPTER 7 WATER QUALITY FAILURE DETECTIONAND LOCATION MODEL

## 7.1 Background

In previous chapters, it is appreciated that precautionary prognostic analyses help to avoid a significant number of water quality failure events. In spite of continuous efforts, a significant number of WQF events happen regularly in Canada and elsewhere. Whatever might be the reasons of a failure, if it is identified and controlled in a minimal time after its occurrence, consumer health and safety risk can be reduced.

From the time of occurrence of a WQF in a WDS to its return to a normal water quality condition, the total time can be divided into two components: (a) awareness time, and (b) action time. The awareness time is the time necessary for a utility organization to be aware of the presence of compromised water quality. The action time is the time necessary for remedial actions. The action time can be divided into location time and repair time. The location time is the time necessary for a utility to locate the source of water quality failure after being aware of its existence, and the repair time is the actual time necessary taking a remedial measure of water quality failure. After the awareness of WQF, boil water notice time continues parallel to the action time. During this period precautionary messages are provided to the consumers in the form of boil water advisories, public notices, emails, phones, and newspaper & television advertisements.

After an occurrence of a water quality failure, if the awareness and the action times are minimal, the risk of consumer sickness will be minimal. Figure 7.1 provides a qualitative distribution of the risk of consumers' sickness with respect to awareness and action times. After the occurrence of a WQF event, the risk of consumer sickness increases exponentially up to the end of awareness time of the relevant utility. After the awareness of the WQF, the utility company can provide boil water notices to avoid the direct use of contaminated water. This will reduce the risk of consumer sickness significantly. During the boil water notice period, utility companies continue searching for the potential causes, location of failure and take necessary action to fix the problem.

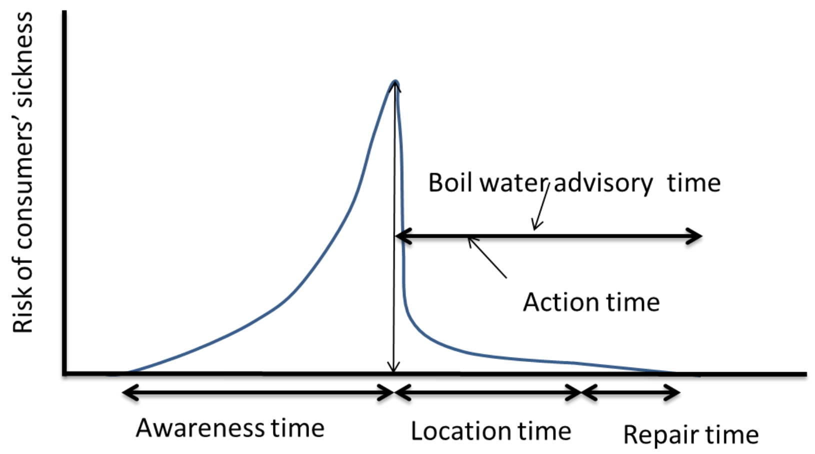



Figure 7.1: Different components of Water Quality Failure Time

In WDS literature, the structural and associated hydraulic failures received more attention than its quality counterpart. Although, the consequence of a WQF event is more severe than a SHF event, the number of studies in the reported literature on the WQF is quite less compared to SHF. Most of the available WQF literatures mainly focus on modelling of the water quality in the distribution system. A limited number of studies are reported on WQF source identification and diagnosis of WQF. A summary review of WQF investigations has been provided in Chapter 2 and Chapter 6.

In this chapter, the methodology for WQF potential evaluation (Chapter 6) model has been extended:

- to identify the presence of a WQF and identify the most probable cause(s) of WQF
- to identify the most probable origin of the identified cause(s) of WQF and ingress concentration
- to identify the most severely affected areas in WDS.

In Chapter 6, a WQF potential model has been proposed where all the necessary information, especially information on the causes of WQF in different locations in the WDS is assumed to be available. In reality, it is unlikely to find such huge volume of data. Therefore, to identify the most probable causes of WQF using WQF potential model, a limited number of sensor data together with simulated results from multi-species water quality modelling tool, EPANET-MSX, has been used. The **P**arameter **EST**imation tool, PEST (Doherty 2005) has been used to identify the most probable origin and ingress concentration of the cause of WQF. Using WQF potential model together with the simulated ingress matrix, the most severely affected area has been identified. Finally, a standalone proof of concept has been demonstrated using a case study.

## 7.2 Materials and Methods

The proposed methodology has six major steps, namely, (a) data collection, (b) hydraulic and multi-species exchange water quality model development, (c) WQF potential model development, (d) water quality failure detection (e) contaminant source tracking using PEST and, (f) identification of the most severely affected area in the WDS. Figure 7.2 shows the overview of the different steps of the proposed methodology and key components in each step. Details of the different steps have been discussed in the following sections.

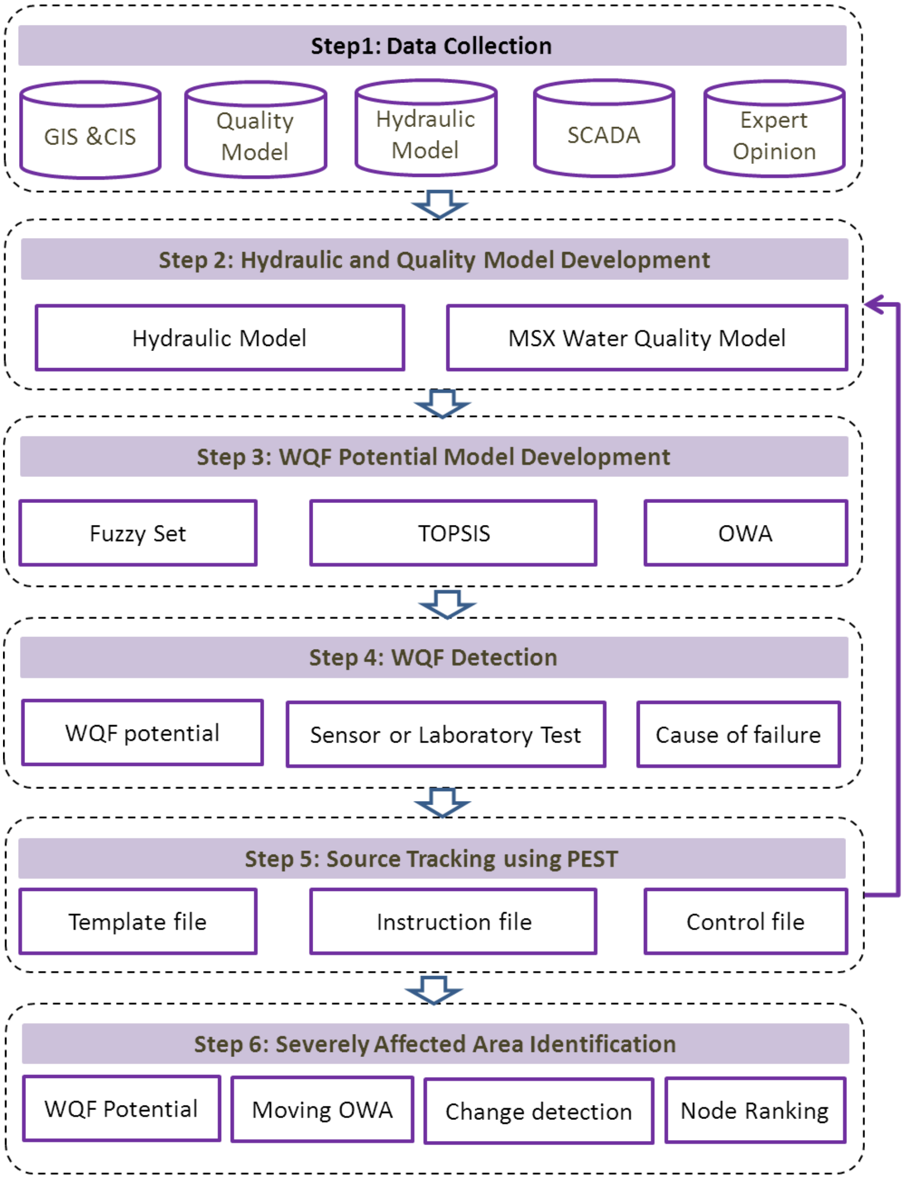



Figure 7.2: Overview of the proposed methodology

### 7.2.1 Data Collection

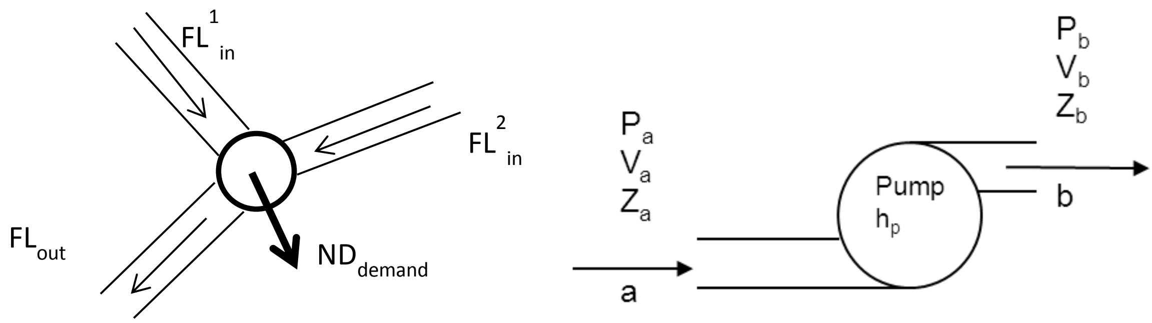
Required data for this model include hydraulic and water quality data, WQF potential model data and observed sensors data. Hydraulic model data include physical properties of WDS including pipe diameters, pipe roughness, water sources, tanks, controls mechanisms for storage facilities and pumps. For a well-managed WDS utility, these data can be collected from the available GIS records, CIS records and different types of design documents. Water quality data include chemical concentrations at inlets and different locations in the system, decay constants, and interaction mechanisms of different chemical compositions. In addition to hydraulic and water quality data, the WQF potential model requires different experts' opinion regarding the interaction of *causes* and *symptoms* of WQF and finally, the sensor data to compare chemical properties with simulated results. Different components of data collection have been discussed in relevant chapters of this thesis.

### 7.2.2 Hydraulic and Water Quality Model Development

A hydraulic model characterizes the hydraulic state of the pipe network in terms of different independent parameters, provides solutions for different dependent parameters (e.g., pressure at nodes and flow through the pipes). The solution of a WDS is based on continuity and head loss (energy) equations. The continuity equation states that the flow into and out of the system must be the same in a steady system. The continuity equation in a node (Figure 7.3a) of a WDS can be written as follows:

$$\sum FL_{in} - \sum FL_{out} = ND_{demand} \qquad [7.1]$$

where, $FL_{in}$ and $FL_{out}$ are the flow in pipes entering and exiting the node, respectively and $ND_{demand}$ is the nodal demand.




(a) Continuity equation (b) Conservation of energy

Figure 7.3: Conservation of mass (a) and energy (b) (FL=Flow; ND= Nodal demand; V=Velocity; Z= Elevation head; $h_p$= Head added by the pump)

The conservation of energy describes the relationship between the energy loss/ gain and pipe flow. Let us consider a situation shown in Figure 7.3 (b) where water flows from the node *(a)* to the node *(b)*. The pressure, elevation head and the mean velocity at node (a) are $P_a$, $Z_a$ and $V_a$, respectively and the pressure, elevation head and the mean velocity at node (b) are $P_b$, $Z_b$ and $V_b$, respectively. Let us also consider that the total friction and fitting head losses from node *(a)* to node *(b)* are HL, and the pump's head is $h_p$. The energy conservation equation (Figure 7.3 (b)) can be written as follows:

$$P_a + Z_a + \frac{V_a^2}{2g} + h_p = P_b + Z_b + \frac{V_b^2}{2g} + HL \qquad [7.2]$$

For WDS with $l_p$ loops, $p_n$ pipes and $n_d$ nodes ($p_n$=$l_p$+$n_d$-1) with pipe diameter $d_p$ ($p=1, 2 ...p_n$), pipe length $L_p$ (p= 1, 2 ...$p_n$) and nodal demand, $ND_n$ ( n=1, 2, 3 ,.. $n_d$), Equation (7.1) and (7.2) can be solved to calculate flow and pressure for all pipes and nodes, respectively. In this study, instead of analytical solutions, EPANET (Rossman 2000) simulation engine has been used to solve these equations. EPANET uses "hybrid node-loop" approach which is also known as "Gradient Method"(Rossman 2000). Detail of EPANET simulation algorithm has been described in the users' manual of EPANET (i.e., Rossman 2000).

The EPANET simulation engine can also model the water quality behaviour in a WDS over an extended period of time. The governing equations for solving water quality are based on the principles of conservation of mass coupled with reaction kinetics (Rossman et al. 1993). The modelling capacity of the current version of EPANET is limited to just a single chemical specie, such as free chlorine used in a disinfectant decay study or any chemical having an appropriate decay rate (including zero decay). However, in reality a WDS needs to deal with multiple interacting chemical species (Shang and Uber 2008). To address this problem, Shang et al. (2007) developed a general framework to model the reaction and transport of different interacting chemicals in a WDS. The developed framework has been implemented as an extension of EPANET programmer's toolkit as a library function which is also referred as EPANET-MSX (**M**ulti-**S**pecies E**X**tension). For this study, multiple interacting chemical interactions have been modelled using EPANET-MSX programmers' toolkit.

In EPANET-MSX, all the reaction dynamics, fast/ equilibrium and conservation of mass, are expressed using differential-algebraic equations. These differential equations express the interactions between the bulk species, surface species, and different parameter values. Equations 7.3 to7.5, provide the general form of differential algebraic equations (Shang et al. 2007):

$$\frac{dx_b}{dt} = f(x_b, x_s, z_b, z_s, p) \qquad [7.3]$$

$$\frac{dx_s}{dt} = g(x_b, x_s, z_b, z_s, p) \qquad [7.4]$$

$$0 = h(x_b, x_s, z_b, z_s, p) \qquad [7.5]$$

where, *x* and *z* are the vectors of time-varying differential variables and time-varying algebraic variables, respectively and *b* and *s* indicate their association with the bulk water and pipe surface respectively and *p* is the time invariant model parameter. To model a set of chemical species, reactions of these chemical species must be in the above forms. Details of water quality modelling using EPANET-MSX simulation engine are available in EPANET-MSX user manual (Shang and Uber 2008).

### 7.2.3 WQF potential Model development

Details of WQF potential model development and its application have been discussed in Chapter 6. No further discussion has been provided in this chapter.

### 7.2.4 WQF Detection

The presence of a significant water quality event can be identified in the sensor locations. Using WQF potential model, WQF potentials are evaluated in the sensor nodes over the time. From the variation of WQF potentials, the presence of a water quality anomaly can be identified. In addition, a regular or special laboratory test results could be an important source of information to identify the most probable causes of water quality failure.

### 7.2.5 Source Tracking Using PEST

After the identification of a contaminant in WDS, the parameter estimation software package, PEST (**P**arameter **EST**imation) has been used to source track the detected contaminant. PEST is the industry standard open source public domain, model-independent parameter estimation and uncertainty analysis software package developed by Watermark Numerical Computing. It has powerful capacity to manage a large number of parameters and to optimize different parameters by searching for either maximum or minimum value of an objective function (Baranowski and LeBoeuf 2006). According to Doherty and Hunt (2010), it has capacity to accommodate hundreds, or even thousands, of parameters in calibration / optimization process without any issue of numerical stability, and it provides a guarantee of parameter reasonableness. To calibrate or optimize a parameter, it interacts with model input and output parameters without accessing to the original model algorithm. To optimize the objective function, PEST uses the *Gauss–Marquardt–Levenberg* algorithm which evaluates the weighted sum of squared differences between observed and model computed outputs (Doherty 2005). Figure 7.4 shows the general workflow of PEST optimization.

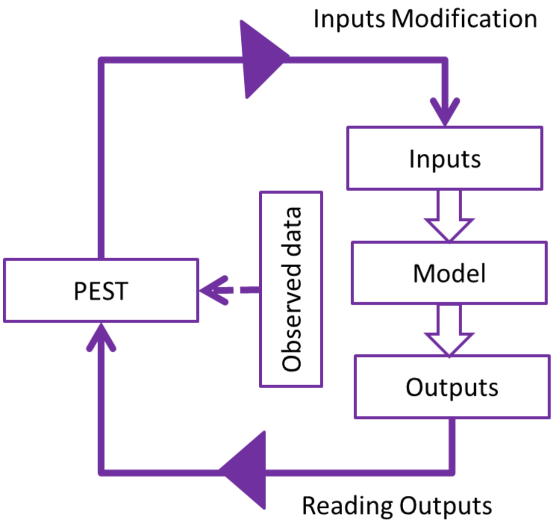



Figure 7.4: Work flow of PEST optimization

At the beginning, the original model is simulated using necessary input parameters and hereafter, PEST compares the observed data with simulated outputs and estimates the weighted sum of squared differences (WSSD) between observed and simulated outputs. If the estimated WSSD is not acceptable, PEST changes the input parameter based on the given instructions and simulate the model again. The acceptability of the WSSD is evaluated by comparing the parameter change and objective function improvement achieved in the current iteration and previous iteration.

PEST software package has been used in various model calibrations in various complex modelling environments. It has been adapted in some popular commercial software to automate the calibration process of their model (e.g., GMS from AQUAVEU). Bahremand and Smedt (2008) have used PEST for the sensitivity analysis of the model parameters of a distributed hydrological model. Numerous applications of PEST have been reported in the literature. However, most of these applications are related to groundwater modelling, hydrological modelling, or irrigation demand modelling. Baranowski and LeBoeuf (2006) have used different optimization techniques to evaluate optimal demand to reduce the contaminant concentration in in a water distribution system. From the comparative analysis of three optimization techniques- (i) an unconstrained first-order reliability method (FORM) (ii) a constrained FORM; and (iii)

PEST package, Baranowski and LeBoeuf (2006) concluded that PEST is the best approach among them with greater capabilities in determining the most optimal solution.

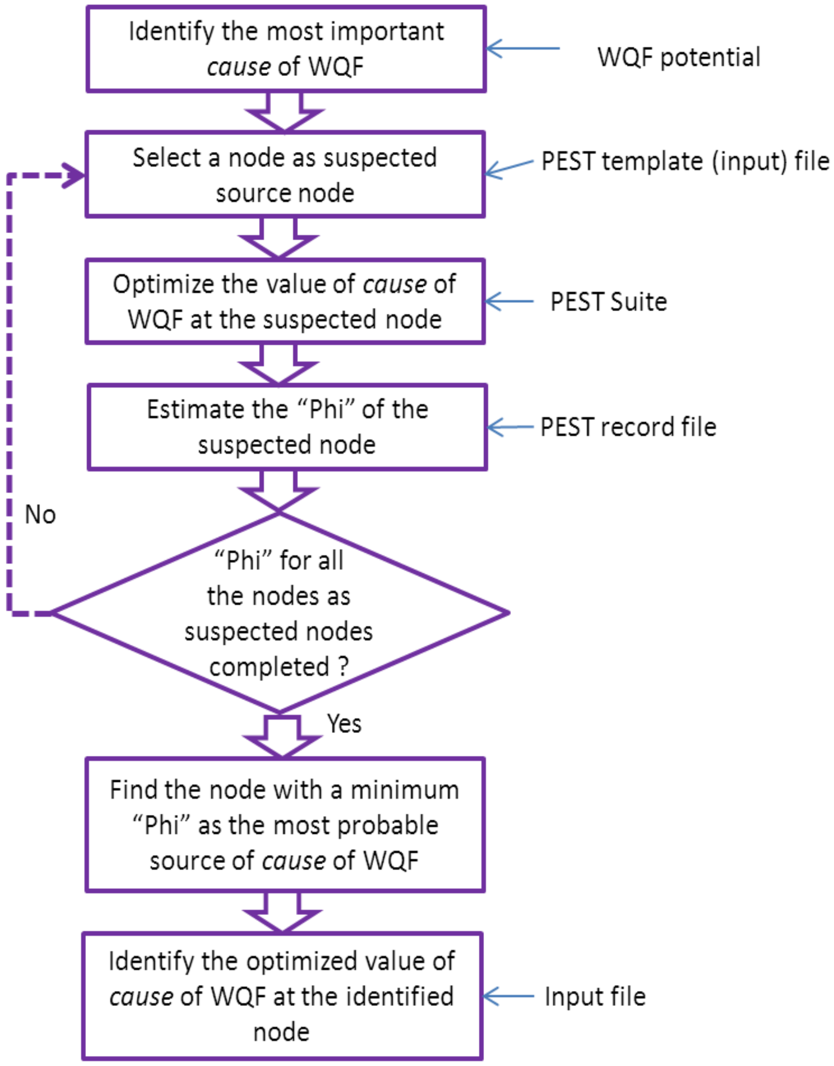



Figure 7.5: Flowchart for PEST implementation to identify the most probable sources of water quality event

Following the guidelines provided by Khalsa and Ho (2008), PEST has been used to identify the most probable origin and its ingress rate of the detected contaminant. To identify the origin of a contaminant source, a list of suspected origins/ sources[22] is created. PEST optimizes the water quality parameter considering a suspected node as a most probable origin of water quality failure. During each optimization, PEST estimates the minimum objective function, the sum of squared

[22] A suspected origin list consists of a set of selected nodes based on any prior information or all the nodes exist in the water distribution system which could be potential origin of the identified contaminant ingress.

weighted residuals, "Phi" for all the suspected nodes. A suspected node which has the *smallest* of the minimum objective functions, "Phi", is considered as the most probable origin of contaminant ingress. The estimated concentration for the most probable origin of the contaminant ingress is also identified during this process. Figure 7.5 shows different steps used for source tracking.

### 7.2.6 Severely Affected Area Identification

After the identification of ingress matrix (origin and concentration), hydraulic and water quality behaviors of the WDS have been simulated. These simulation results provide necessary information to estimate WQF potential in different nodes in the WDS. Due to the nodal physical, chemical and demand heterogeneity, each node WQF potential has been lumped by multiplying surrounding water volume at each node in terms of (%-volume). Figure 7.6 shows the zone of influence of a node used to estimate the volumetric WQF potential.

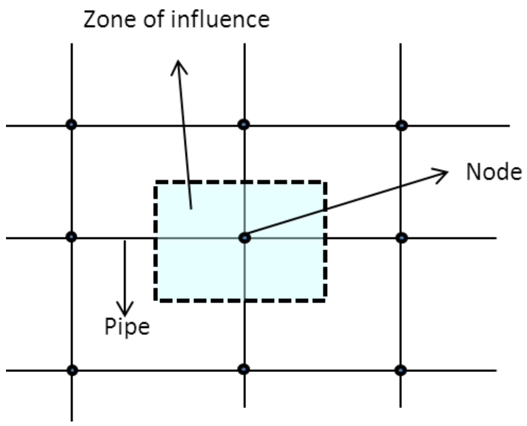



Figure 7.6: Zone influence

From the volumetric WQF potentials, the relative importance of a node has been evaluated with respect to the volumetric WQF potentials of the surrounding nodes. During this evaluation OWA has been applied with the highest weight of given to the node of concern. The procedure has been applied to the all nodes or preselected suspected nodes. This will provide a new set volumetric WQF potentials containing influence of surrounding nodes.  Figure 7.7 shows the different steps involved to identify the most severely affected areas in a WDS. Following above procedure, a node with highest value of volumetric WQF potential is considered as the most severely affected node in the WDS. As a cross check of this approach, the relative changes of different parameters of a particular node during base condition (normal quality condition) and a potential failure condition are compared. This comparison can also identify the most severely affected area in distribution system.

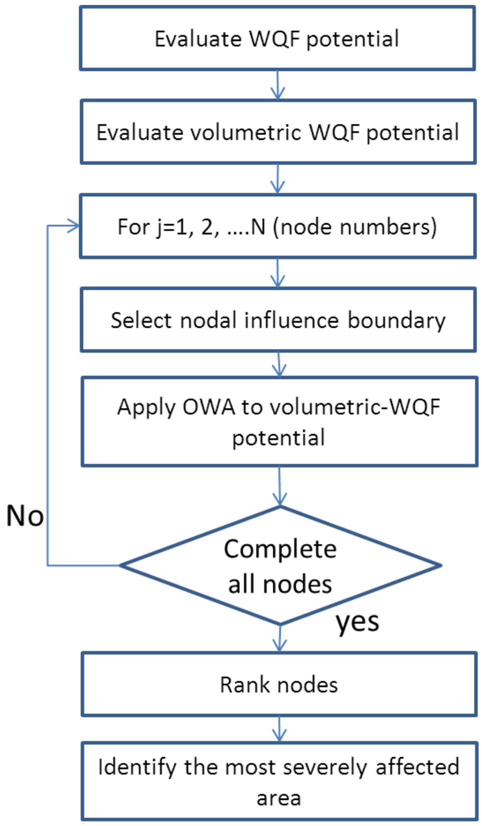



Figure 7.7: Flowchart for detecting the most probable source node of WQ failure

## 7.3 Model Implementation

To demonstrate the proof of concept, the developed model has been implemented and demonstrated using an example WDS. Iron based metallic pipes have been intentionally considered to represent the reaction of arsenic. Water is supplied by gravity from the two elevated reservoirs (reservoir 1 and reservoir 2) with the total head of 90 m, and 85 m, respectively. The lengths of the pipes vary from 100 m to 680 m, and the diameters of the pipes vary from 200 mm to 700 mm. Base demands at different nodes varies from 50 l/s to 100 l/s and demand multipliers ranges from 0.38 at 5am to 1.46 at 9 am. Detail information on pipe length, diameter, roughness coefficient, nodal connectivity, and nodal hourly base demand and demand multipliers and two reservoirs head have been provided in Table 3.6 in Chapter 3.

Under normal operating conditions, there is no major quality issue. Initial chlorine concentrations from both reservoirs ensure the minimum chlorine concentration at all nodes in the system. As a hypothetical scenario, an intentional contamination with Arsenic in the WDS is assumed which react with the disinfectant residual monochloramine (NH2Cl). To avoid modelling complexity, the initial concentrations of monochloramine at the both reservoirs are also assumed (2.5μm/L).

The hydraulic and water quality conditions are modelled using the EPANET and EPANET-MSX which estimates hydraulic and water quality properties at nodes and pipes of the WDS. The additional information which cannot be modelled using EPANET and EPANET–MSX are considered same used in Chapter 6. The observed data for both normal and arsenic contamination events have been generated using the EPANET and EPANET–MSX.

### 7.3.1 Modelling of Fate of Arsenic in WDS

In Chapter 6, a list of 17 parameters has been identified which *causes* WQF in WDS. It is impractical to collect data for all the parameters at all locations of a WDS. Therefore, for water quality modelling, an EPANET-MSX model has been developed. In addition, due to the modelling complexity, it is difficult to model all the identified interacting water quality parameters. The proposed methodology has been demonstrated using an example taken from Shang and Uber (2008) which represents contamination of drinking water by an intentional injection of arsenic into the WDS.

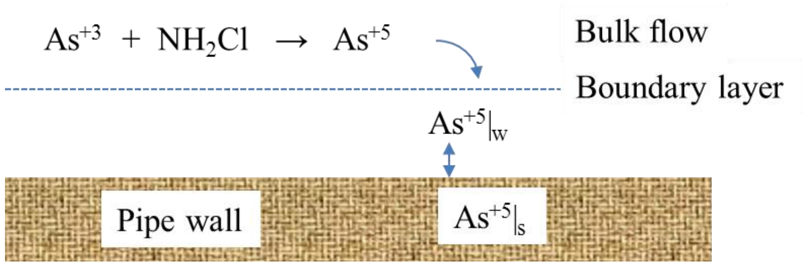



Figure 7.8: schematic of Arsenic oxidation/ adsorption in the water distribution system (source: (Shang and Uber 2008)

This example shows the oxidation of the intentional contaminate arsenic from its arsenite ($As^{+3}$) to arsenate ($As^{+5}$) by the influence of monochloramine disinfectant residual in the bulk flow. The developed EPANET-MSX model simulates the different interacting reactions between arsenic and monochloramine in bulk flow, boundary layer and pipe surface. Figure 7.8 shows the schematic of Arsenic oxidation/ adsorption in the water distribution system. The mathematical form of the reactions has been expressed in terms of five differential rate equations (Gu et al. 1994; Shang and Uber 2008):

$$\frac{dAs^{+3}}{dt} = -k_a As^{+3}(NH_2Cl) \qquad [7.6]$$

$$\frac{d(NH_2Cl)}{dt} = -k_b(NH_2Cl) \quad [7.7]$$

$$\frac{dAs^{+5}}{dt} = k_a As^{+3}(NH_2Cl) - K_f A_v(As^{+5} - As_w{}^{+5}) \quad [7.8]$$

$$\frac{dAs_w{}^{+5}}{dt} = K_f A_v(As^{+5} - As_w{}^{+5}) - A_v[k_1(S_{\max} - As_s{}^{+5})As_w{}^{+5} - k_2 As_s{}^{+5} \quad [7.9]$$

$$\frac{dAs_s{}^{+5}}{dt} = k_1(S_{\max} - As_s{}^{+5})As_w{}^{+5} - k_2 As_s{}^{+5} \quad [7.10]$$

where $As^{+3}$ is the arsenite concentration in the bulk water, $As^{+5}$ is the arsenate concentration in the bulk water, $As_s^{+5}$ is the arsenate concentration in pipe surface, $As_w^{+5}$ is the arsenate concentration adjacent to the pipe wall (bulk), $NH_2Cl$ is the monochloramine concentration in the bulk water, $k_a$ is the rate coefficient for the arsenite oxidation, $k_b$ is the rate coefficient for monochloramine decay, $A_v$ is the pipe surface area per liter pipe volume, $k_1$ and $k_2$ are the rate coefficients for arsenate adsorption and desorption respectively, $S_{max}$ is the maximum pipe surface concentration of arsenate, and $K_f$ is the mass transfer coefficient dependent of the amount of turbulence in pipe and diameter of the pipe. The value of $K_f$ is estimated using Equation 7.11 shown as follows:

$$K_f = \frac{1.6\times10^{-4}\,\mathrm{Re}^{0.88}}{D} \quad [7.11]$$

where Re is the Reynolds number and D is the diameter of the pipe.

To use EPANET-MSX, reactions are converted in the form of Equations 7.3, 7.4 and 7.5. According to Shang and Uber (2008), in case of reversible sorption processes, a local equilibrium assumption (LEA) is sometimes assumed between the concentrations in the bulk and the adsorbed phase (i.e., $\frac{dAs_s{}^{+5}}{dt} = 0$). Therefore, the Equation 7.10 can be expressed as an algebraic equation as shown in Equation 7.12.

$$As_s^{+5} = \frac{k_s S_{\max} As^{+5}}{1 + k_s As^{+5}} \qquad [7.12]$$

Where $k_s=k_1/k_2$.

Therefore, the Equations 7.6 to 7.9 and Equation 7.12 are the required form of reactions (rate equations and one algebraic equation) which have been modelled using EPANET-MSX. In the above five equations, the respective terms for Equation 7.3, 7.4 and 7.4 are, $x_b$=[$As^{+3}$, $As^{+5}$,$As_w^{+5}$,NH2Cl], $x_s$=[Ø] , $z_s$=[$As_s^{+5}$], p=[$k_a$, $k_b$, $A_v$, $k_1$, $k_2$, $K_f$, $S_{max}$]. A further details of the modelling multi-species as this example, are available in Shang and Uber (2008).

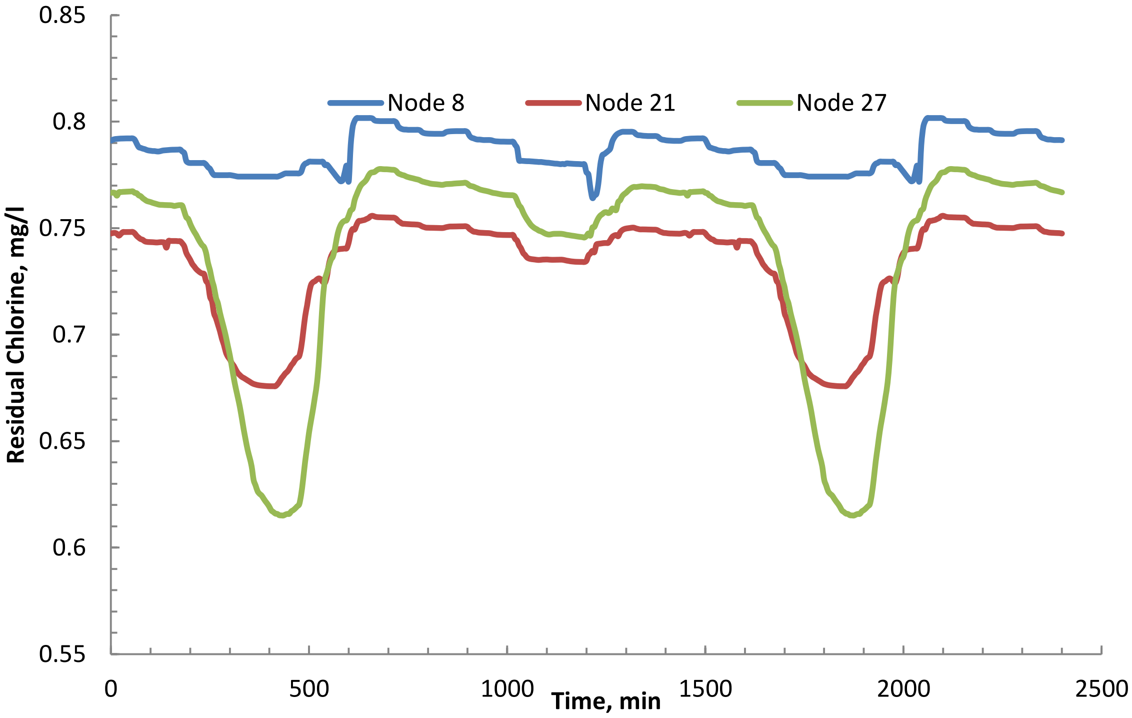



Figure 7.9: Residual chlorine concentration at nodes 8, 21 and 27

In addition, it is assumed that the chlorine decay is only due the bulk water and wall decay. The reaction of bulk and wall decay has been modelled using the equation as shown below:

$$\frac{\delta C}{\delta t} = -k_b.C - \frac{4.k_w.k_f}{D(k_w + k_f)}.C \qquad [7.13]$$

where, *C* is the chlorine concentration, $k_b$ is the bulk water decay rate, $k_w$ is the pipe water decay rate, $k_f$ is the mass transfer coefficients, D is the pipe diameter. Figure 7.9 shows residual chlorine at node 8, 21 and 27 for typical two consecutive days.

### 7.3.2 Water Quality Event Data Preparation

As the proposed methodology has been demonstrated using an example WDS, therefore, the observed data have been generated by simulating arsenic contamination event using the EPANET-MSX model. To represent contamination of water due to arsenic ingress, arsenic has been added in the system constantly at the rate of 10µgm/L randomly from the node no. 7.

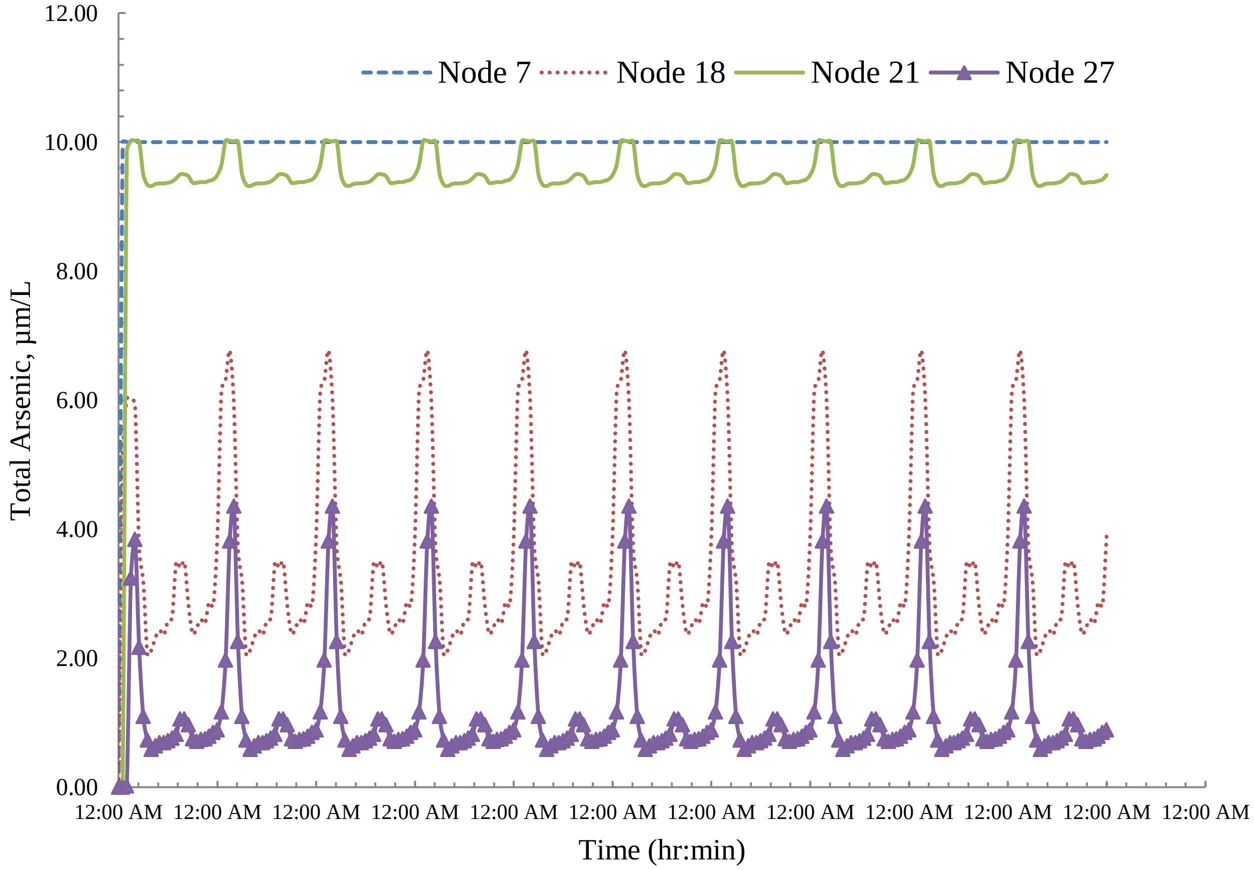



Figure 7.10: Total Arsenic concentration at different nodes in the network

The simulation results of a node can be considered as an observed arsenic concentration in that particular node. For this study, arbitrarily sensors have been assumed in five locations in the WDS at nodes 4, 18, 21 and 27. The simulated results from these nodes are considered as observed data and have been used in the source tracking. It is noted that the number of observed nodes depends on the network size and types of chemicals. For a successful source tracking, the contaminant in the system must have impact on the observed data. If the contaminant ingress cannot influence the observed data, the model will not be able to perform its intended objective. Therefore, optimum number of sensors is required to monitor the observed data. The number of optimum sensors has not been covered in this thesis. Figure 7.10 shows the time varying total Arsenic concentration of $As^{+3}$ at the ingress node (Node 7) and other three nodes (i.e., node no. 18, 21 and 27).

### 7.3.3 WQF Detection and Source Tracking Using PEST

After the detection of arsenic, PEST has been used to identify the most probable origin of arsenic in the system. To source track back, PEST package requires three input files which are (a) the template file (*.tpl) (b) the instruction file (*.ins) and (c) the control file (*.pst).

As a part of optimization, PEST runs the model using various combinations of input variables and minimizes / maximizes its objective function. To change the input variables during optimization, PEST requires guidelines what to change. The template file (*.tpl) contains the guidelines which tell the PEST what parameters are required to change. A template file is based on the model input file which has at least one optimizing parameter. In this case, EPANET-MSX input file '*.msx' is converted to template file. Detail instruction for the creation of template file has been provided in Doherty (2005). Instruction file is another prerequisite input file to run PEST package. It provides instructions to PEST, how to read the simulated data from the output file to compare with the observed data. In this study, the outputs are taken from EPANET-MSX output file. Again, detail for creating an instruction file has been provided in Doherty (2005). The third important PEST input file is a control file. A control file combined everything together including information from template and instruction files. It assembles the model names and its execution command, parameter names and their initial values, observed data, template file and corresponding input file, instruction file, and a number PEST variables which control the implementation of the Gauss-Marquardt-Levenberg method (Doherty 2005).

After configuring input files, PEST has been run to optimize ingress dose considering node 1 (reservoir 1) as a first suspected node for ingress. It is noted that PEST keeps records for all the calculation in the "*.rec" file in the PEST simulation directory, and after optimization it left the input file with the optimized parameters' values. After the PEST run for the first suspected node, the PEST "*.rec" file are checked which contains the sum of squared weighted residuals (i.e., phi). The optimized parameter for a particular suspected node has the lowest value of "Phi". For the first suspected node (i.e., reservoir 1), the estimated minimum value of the sum of squared weighted residuals (i.e., Phi) =7.417 and the estimated ingress concentration is 9.65µg/L. The procedure continues for the all the suspected nodes one by one. The most probable source of ingress node is the one which has an absolute minimum value of “Phi” and corresponding concentration is the ingress rate. In this example, the estimated absolute minimum value (minimum value of all minimum values) of sum of squared weighted residuals (i.e., Phi) is 9.0000E-04 and the estimated ingress concentration is 10.0001 µg/L. These values were estimated considering node 7 as a suspected node which is nothing but the node where the ingress rate concentration were used to generate observed data. The estimated ingress concentration was also estimated almost 100% accuracy. The whole procedure has been automated writing a Matlab program which can finally identify the most probable ingress sources and ingress concentration.

### 7.3.4 Identification of the Most Severely affected Area in WDS

It is not necessarily always true that the ingress node is the most severely affected area. There are many contaminants which have growth inside the WDS, especially, microbiological contaminants. For this type of contaminants the most severely affected node could be the node other than the origin of the contaminant. In that case, after the identification of the most probable location and dose of contaminant ingress, EPANET-MSX model have been used to simulate the contaminant at the different location of WDS. The most severely affected area need to be identified using WQF potential model as described earlier. However, in this case, as the arsenic has a decay rate rather a growth rate inside the distribution system, therefore, the ingress node 7 was also identified as the most severely affected node in the system. However, during an attempt to simulate bacterial intrusion in the distribution system, it was found that node 27 is the most severely affected node due to microbial contamination in the distribution system.

## 7.4 Model Summary

This chapter discussed the WQF detection and diagnosis methodology. The model has a capacity to identify the presence of any contaminant intrusion into a WDS. It has also capacity to identify the most probable origin of the contaminant intrusion and a most possible ingress rate in the system. It also has the capacity to identify the most severely affected area in a WDS. The developed model has been implemented on an example WDS to demonstrate its applicability for arsenic intrusion from a single ingress node. From the analysis, it is seen that the developed model can fulfill its objectives by detecting presence of contaminant intrusion and its ingress matrix. The developed model can be used for any real WDS by modifying appropriate factors / parameters. Although the proposed methodology can detect and diagnosis a water quality event in WDS, the interaction of multiple chemical ingress has not been investigated. The detection methodology is based on the change in output parameters. Therefore, if the ingress rate is very small and or ingress contaminant reacts very slowly there might be some difficulty in detection.

# CHAPTER 8 INTEGRATED DICISION SUPPORT SYSTEM

## 8.1 Background

An integrated prognostic and diagnostic analysis framework consisting of various novel models and existing best management practice tools has been proposed in Chapter 2. The development of different models and their standalone applications through case studies have been discussed in Chapter 3 to Chapter 7. In this chapter, a methodology has been developed to integrate the outputs of the developed models and existing available information. Although different models have been developed under the framework of fuzzy set theory, the integration of the models has been carried out under the framework of Dempster–Shafer (D-S) theory of evidence (Shafer 1976). One of the most important reasons for switching from Fuzzy set theory to the D-S theory is number of parameters involved in different models. Using fuzzy set theory, it was difficult to make the integrated framework sensitive to different parameters due to the huge volume of data. However, D-S theory provides better results in this case.

## 8.2 Framework Integration

Figure 8.1 shows the conceptual integration of the proposed framework. This framework is a holistic view of WDS system management tools. According to the modes of failures, the integration process has been categorized into hydraulic and water quality components. In another hand, based on the modes of investigation, the integration process has been categorized as prognostic investigation and diagnostic investigation. Considering modes of failure and types of investigation, the integration process has four parts consisting of hydraulic prognostic investigation (H, P), hydraulic diagnostic investigation (H, D), water quality prognostic investigation (Q, P), and water quality diagnostic investigation (Q, D). For the hydraulic prognostic investigation, integrated hydraulic state of the WDS has been evaluated based on the outputs of leakage potential model, calculated hydraulic utility (disutility) model and historical pipe burst data. The sources of this information have been mentioned at the bottom of relevant boxes in Figure 8.1.

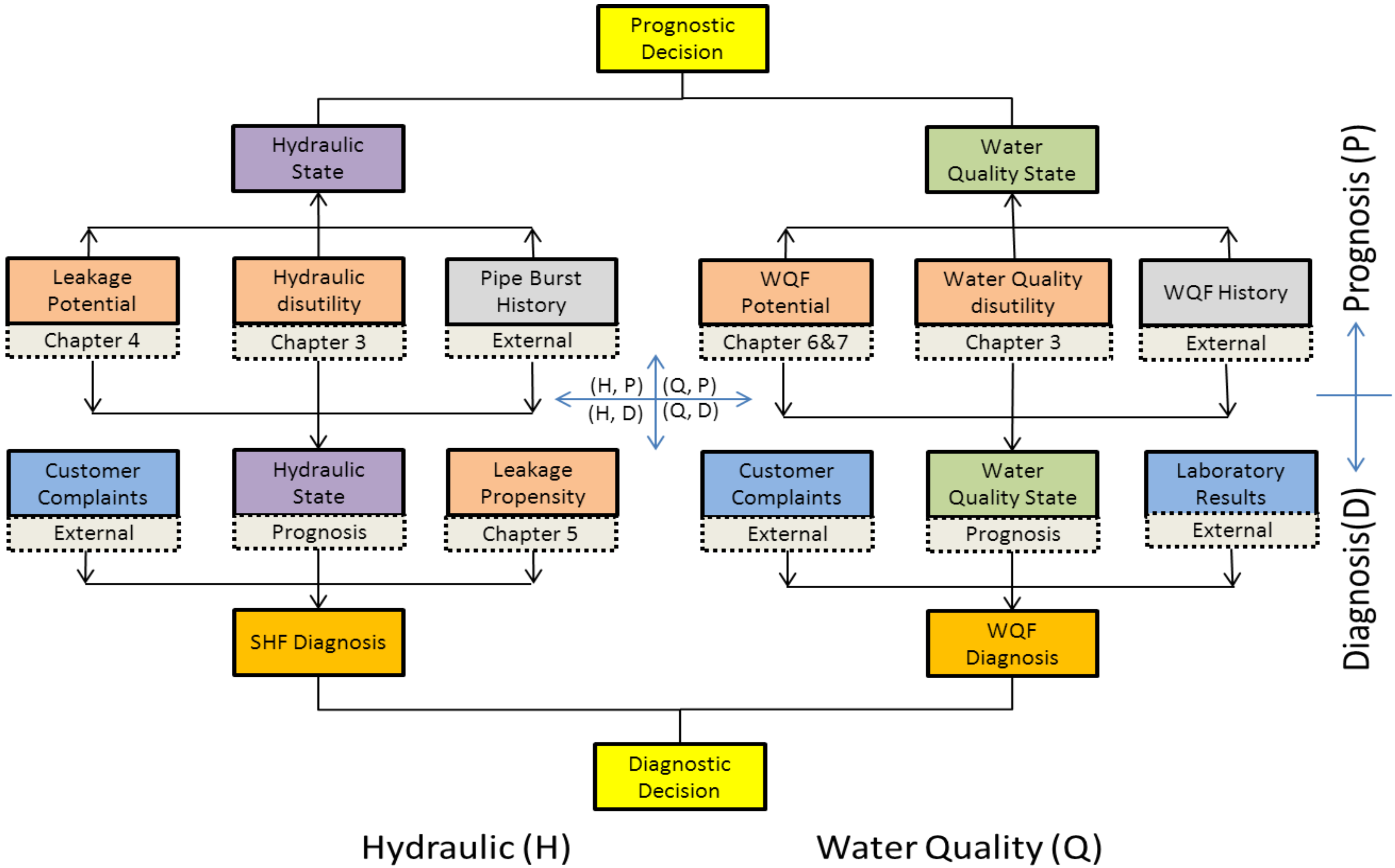



Figure 8.1: Conceptual integration of proposed framework

Details of the leakage potential model have been described in Chapter 4, and as part of the reliability assessment methodology, the evaluation of hydraulic utility has been described in Chapter 3. It is noted that instead of hydraulic utility, hydraulic disutility which is the complement of hydraulic utility has been used in the integration process. The historical pipe burst information from the utility regular data repository has been used as an external source of information. The hydraulic diagnostic investigation which identifies the most probable location of hydraulic failure is based on the hydraulic state of WDS (prognostic investigation), consumer complaints and the leakage propensity evaluated in Chapter 5. Although the evaluated leakage propensity can identify the most probable location of hydraulic failure independently, the integration of consumer complaints and prognosis investigation results will enhance the confidence on the decision.

Similar to the hydraulic state, integrated water quality state of WDS has been evaluated based on the WQF potential model results, water quality utility (disutility) model results and historical WQF data. Development and evaluation of WQF potential and WQ utility have been described in Chapter 6 and Chapter 3, respectively. Similar to the hydraulic disutility, the water quality disutility has been used in the water quality state estimation. The historical water quality failure data from the utility's regular data repository have been used as an external source of information. The water quality diagnostic investigation identifies the most severely affected locations in a WDS based on the water quality state of the WDS (prognostic investigation), consumer complaints and available laboratory water quality test results. Data coming from the different models have been used directly in the integration process. However, historical pipe burst data, historical WQF data, hydraulic and water quality consumer complaints and water quality laboratory test results have been harmonized. Due to the variation of the importance of data in space and data type, the two adaptation factors called, E*quivalent on Spot Complaints (ESC)* and *Equivalent Illness Complaints (EIC)* have been introduced. While ESC has been used to harmonize the spatial issues, EIC has been used to harmonize different types of water quality complaints and laboratory test results. The concepts of ESC, EIC and D-S theory of evidences and their implementation in the integration process have been described in the following sections. Finally, an integrated decision support system has been developed based on the model results and harmonized data.

## 8.3 Equivalent on Spot Complaint (ESC)

The complaints received by water companies are spatially distributed. Bicik et al. (2011) mentioned that the consumer complaints are strong indicators of water distribution failure. However, all of them are not trustworthy with a same confidence level. A complaint received from the spot of the failure shall have a higher level of confidence than a complaint received from other than the failure location.

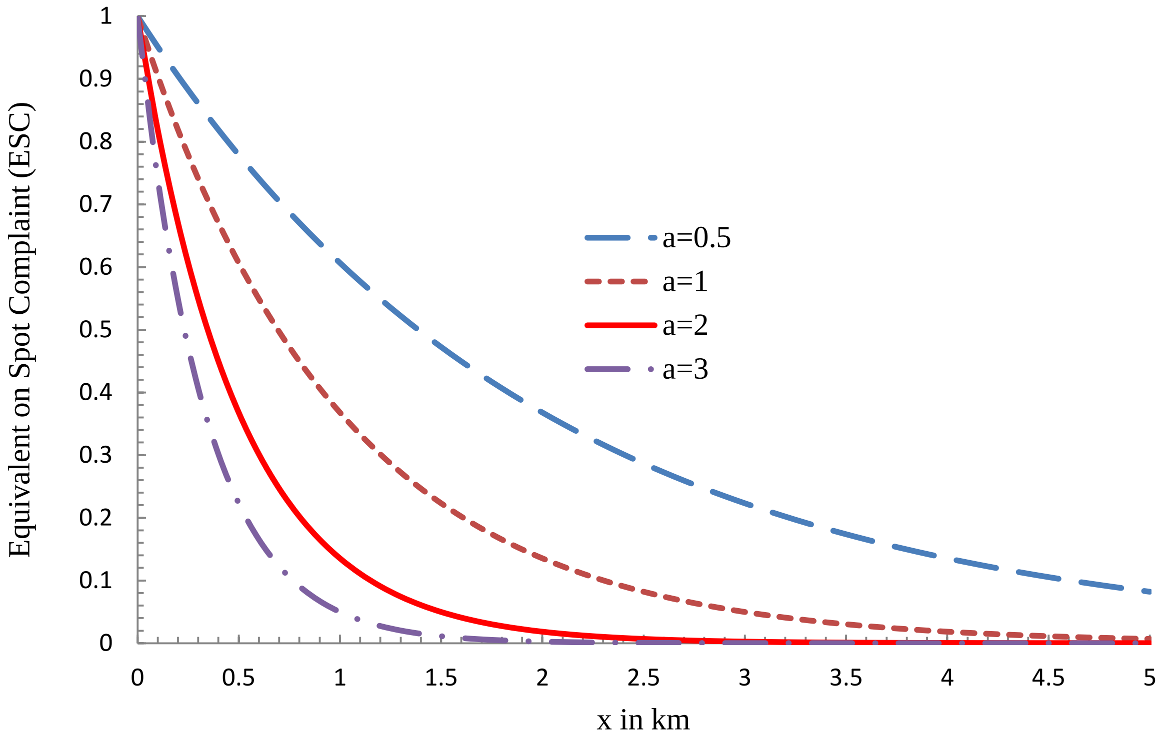



Figure 8.2: Variation of an ESC with complaint distance and constant, *a*.

Therefore, different complaints such as pipe burst complaints and water quality complaints have been converted to an equivalent on spot complaint (ESC). An ESC has been defined as a complaint which has a confidence level equivalent to a complaint reported from the spot of the failure. Equation 8.1 has been used to estimate an ESC of a complaint:

$$\mathrm{ESC} = e^{-ax} \qquad [8.1]$$

where, $a$ is a constant based on the expert opinion, $x$ is the Euclidian distance from the complaining consumer to the candidate node/ pipe in km. Figure 8.2 shows the variation of ESC under variable $x$ and $a$. The distance, $x$ is constant for a particular complaint and a decision maker has no control over it. However, a decision maker can model his attitude to the confidence level by controlling the parameter, *a*.

### 8.4 Equivalent Illness Complaints (EIC)

In Chapter 6, a list of nine *symptoms* and 17 *causes* of water quality failure has been identified. A water company may receive consumer complaints for any of these water quality issues, even further. However, the severities of these complaints are not same. A complaint for bad taste does not have the same severity for a complaint for reported waterborne disease. A common scale termed as Equivalent Illness Complaint (EIC) has been introduced to address the variation of different types of water quality complaints. An EIC has been defined as a water quality complaint which has a severity level equivalent to a complaint that causes illness for the consumers. Equation 8.2 has been used as measured EIC of a water quality complaint.

$$\mathrm{EIC} = \sum_{i=1}^{N} C_i \times W_i, \quad \text{where, } W_i \in (0,1) \qquad [8.2]$$

where $i$ is the different types of complaints, $C_i$ is the number of different types of complaints, and $W_i$ is the weight of the each complaint with respect to a complaint of illness to the consumer. Although a decision maker has no control on the number of different types of complaints, a decision maker can model his attitude by controlling $W_i$ based on their expert judgments.

### 8.5 Dempster–Shafer Theory

Dempster-Shafer (D-S) theory is a mathematical evidence theory and considered as a generalization of the Bayesian approach (Sadiq et al. 2006a). The groundbreaking work was introduced by Dempster (1967) and extended by Shafer (1976). In the Bayesian approach, the summation of a “hypothesis”, p (A), and a “not hypothesis”, p (not A), is one, (i.e., p (A) + p (not A) =1). A belief in a hypothesis A can be used to derive the belief in its complement without any evidence of its complement based on this relationship. In this case, ‘‘not A’’ is the missing evidence (lack of knowledge) but this complement, ‘‘not A’’ is evaluated with an equal confidence of “p (A)”. Therefore, some researchers argued that ‘‘no evidence’’ is different from having degree of confidence in a certain hypothesis and this argument is the basic motivation behind D–S theory of evidence. In D-S theory, evidence is attributed in the form of belief to the subsets in a universe of discourse (Θ). For example, if some evidence “a” is attribute of p (A), the ignorance ‘‘1 -a’’ will not be assigned to p (not A), rather it will be assigned to both {p (A), p (not A)}. D-S theory has been used in various engineering applications including water related applications. Sentz and Ferson (2002) provided a background discussion on D-S theory and a review of different applications of this theory in various fields. Application of this theory in the field of water engineering is relatively new but not rare. Sadiq et al. (2006) used D-S theory to estimate the risk of contaminant intrusion in WDS. Li (2007) used D-S theory for hierarchical risk assessment of water supply system. Bicik et al. (2011) used D-S theory to fuse information collected from three different models to identify the most probable location of burst in a WDS. Sadiq and Rodriguez (2005) discussed basic concepts of D-S theory and applied to interpret drinking water quality in WDS.

Three important concepts - *basic probability assignment, belief function,* and *plausibility* are the souls of D-S theory and operates under on a ‘‘frame of discernment’’, Θ. The “frame of discernment’’ is a set of mutually exclusive alternatives, the space of possible events / options. A belief assigned to individual exclusive alternative is termed as a *basic probability assignment*; also known as *mass function* and expressed as: BPA (A), bpa (A) or m (A). A *basic probability assignment function* ($2^{\Theta} \rightarrow [0, 1]$) satisfies the following conditions:

i. all the beliefs are mapped in the interval of [0 1] , i.e., m (A)→[0 1]
ii. the null set is ‘‘0’’ , i.e., m(φ)=0
iii. the sum of basic probability assignments in a given set A is ‘‘1’, i.e., $\sum_{A\subseteq\Theta} m(A) = 1$

Another important component of the D-S theory is a *belief function (bel)* which is the sum of all *basic probability assignments* of all subsets (B) of the set (A), and mathematically, can be expressed as $bel(A) = \sum_{B\subseteq \mathrm{A}} m(B)$. Based on this relationship, it is also possible to prove that $bel(\phi) = 0$ and $bel(\Theta) = 1$. The third important function of D-S theory is the *plausibility function (pl)* which is nothing but the upper limit of *belief* and the sum of all basic probability assignments of all subsets (B) that intersects with the set of interest (A), and mathematically, can be expressed as $pl(A) = \sum_{B\cap(A)\subseteq\phi} m(B)$. Readers are suggested to consult with different D-S theory based literature (e.g., Bicik et al. 2011; Li 2007; Sadiq et al. 2006; Sadiq and Rodriguez 2005) for the basic discussion and detail interpretation on the D-S theory.

### 8.5.1 Estimation of BPAs

In this study, D-S theory has been implemented to evaluate hydraulic & the water quality state of WDS (prognosis) and diagnostic investigation of different kind hydraulic & water quality failures. In all cases, the frame of discernment consists of two propositions (binary frame of discernment) of different kinds of failures, and described by a universal set, Θ= {L, NL} where *L* represents *likelihood* and *NL* represents *not likelihood* of different kind of incidences. The power set of incidences consists of the following subsets: (ϕ, {L}, {NL}, {L, NL}). In case of hydraulic failure, {L} represents the *likelihood* of hydraulic failure; {NL} represents the *not likelihood* of hydraulic failure and {L, NL} represents complete ignorance about hydraulic failure. In a similar way, the water quality failure frame of discernment has been implemented where {L} represents the *likelihood* of water quality failure; {NL} represents *not likelihood* of water quality failure and {L, NL} represents complete ignorance about water quality failure.

The proposed integration framework (Figure 8.1) has four different phases. In each phase, three different sources of evidences have been used. Table 8.1 shows different sources of evidences used in different phases of integration and their sources of evidences.

Table 8.1: Different phases of Integration

| Phases | Phase names | Evidences | Location of Evidence |
|---|---|---|---|
| Phase 1 | Hydraulic prognosis (H, P) | • Leakage potential model<br>• Hydraulic utility model<br>• Historical pipe burst data | • Pipe<br>• Node<br>• Pipe |
| Phase 2 | Hydraulic diagnosis (H, D) | • Consumer complaints<br>• Hydraulic state<br>• Leakage propensity | • Pipe/Node<br>• Pipe/Node<br>• Pipe/Node |
| Phase 3 | Quality prognosis (Q, P) | • WQF potential model<br>• Water quality utility model<br>• Historical WQF data | • Node<br>• Node<br>• Pipe |
| Phase 4 | Quality diagnosis (Q, D) | • Consumer complaints<br>• Water quality state<br>• Laboratory results | • Pipe/Node<br>• Pipe/Node<br>• Pipe/Node |

In Table 8.1, it is mentioned that some evidences are available along the pipe lengths, some are at nodes, and some can be available both along pipes and at the nodes. For example, the leakage potential and the historical pipe bursts evidences are available along the pipes whereas the hydraulic utilities are evaluated at different nodes. However, the prognostic and diagnostic investigation can be carried out using either nodal or pipe evidences. Therefore, either the nodal evidences are required to convert to the pipe evidences or the pipe evidences are required to convert to the nodal evidences. In this case, the nodal evidences are converted to pipe evidences by averaging nodal evidences of two connecting nodes and the pipe evidences are converted using zone of influences estimated by the half of the connecting pipe length to a node (Figure 7.6).

In both cases, evidences are harmonized based on the appropriate adjustment factors (ESC & EIC). In case of evidence available along a pipe, Euclidian shortest distance from the complaint location to the pipe location and in case of evidence available at a node, Euclidian shortest distance from the complaint location to the node have been used in ESC and EIC calculations. From the homogenized evidences, BPAs have been evaluated using two steps procedure adapted from Safranek et al. (1990). The technique is quite popular and adapted by several investigators in the literature (Bicik et al. 2011; Gerig et al. 2000). However, a fuzzy based approach is also reported in the literature (Sadiq et al. 2006).

At the first step of BPAs estimation, the historical pipe bursts, consumer complaints, historical WQFs, laboratory results and leakage propensities have been converted to normalized confidence factors using a suitable normalization function. However, leakage potential, WQF potential, hydraulic and water quality utilities are already in a scale of (0, 1). Therefore, further normalizations are not necessary for them. Numerous (e.g., Sigmoid, Gaussian, Logit, and even a Linear) normalization functions can be used to estimate equivalence confidence factors. However, a sigmoid function has been adapted for this study. Equation 8.3 shows the sigmoid function used for normalization (Beynon 2005; Gerig et al. 2000):

$$cf_i(v_{j,i}) = \frac{1}{1+e^{-k_i(v_{j,i}-\theta_i)}} \qquad [8.3]$$

where $k_i$ describes the steepness of the function and $\theta_i$ determines the offset of *v* axis. The solutions of this function are controlled by two controlling variables, $k_i$ and $\theta_i$. According to Safranek et al. (1990), above function satisfy following criteria:

(i) $cf_i(v_{j,i})$ is a monotonic increasing (or decreasing) function.
(ii) $cf_i(v_{j,i})$ =1; if the measurement v implies certainty in the hypothesis
(iii) $cf_i(v_{j,i})$ =0; if the measurement v implies certainty in not the hypothesis
(iv) $cf_i(v_{j,i})$ =0.5; if the measurement v favors neither the hypothesis nor not the hypothesis.

The normalized evidences in different phases have been mapped to BPAs for {L}, {NL} and {L, NL} using the following equations (Equation 8.4, 8.5, and 8.6):

$$m_{j,i}(\{L\}) = \begin{bmatrix} 0 & , & cf_i(v_{j,i}) \le A1 \\ \dfrac{B_1}{1 - A_1 - A_2} cf_i(v_{j,i}) - \dfrac{A_1 B_1}{1 - A_1 - A_2} & , & 1 - A_2 > cf_i(v_{j,i}) > A1 \\ B_1 & , & cf_i(v_{j,i}) \ge 1 - A_2 \end{bmatrix} \quad [8.4]$$

$$m_{j,i}(\{NL\}) = \begin{bmatrix} B_3 & , & cf_i(v_{j,i}) \le A_4 \\ B_3 + \dfrac{[cf_i(v_{j,i}) - A_4][B_3 - B_2]}{1 - A_3 - A_4} & , & 1 - A_3 > cf_i(v_{j,i}) > A_4 \\ B_2 & , & cf_i(v_{j,i}) \ge 1 - A_3 \end{bmatrix} \quad [8.5]$$

$$m_{j,i}(\{L, NL\}) = 1 - m_{j,i}(\{L\}) - m_{j,i}(\{NL\}) \quad [8.6]$$

The Equations 8.4, 8.5, and 8.6 are controlled by one variable and seven controlling parameters ($A_1$, $A_2$, $A_3$, $A_4$, $B_1$, $B_2$, and $B_3$; $\subseteq 1$). A decision maker can define these controlling parameters based on their expert judgment. Figure 8.3 shows definition of the controlling variables and the general steps for the transformation of input data into BPAs.

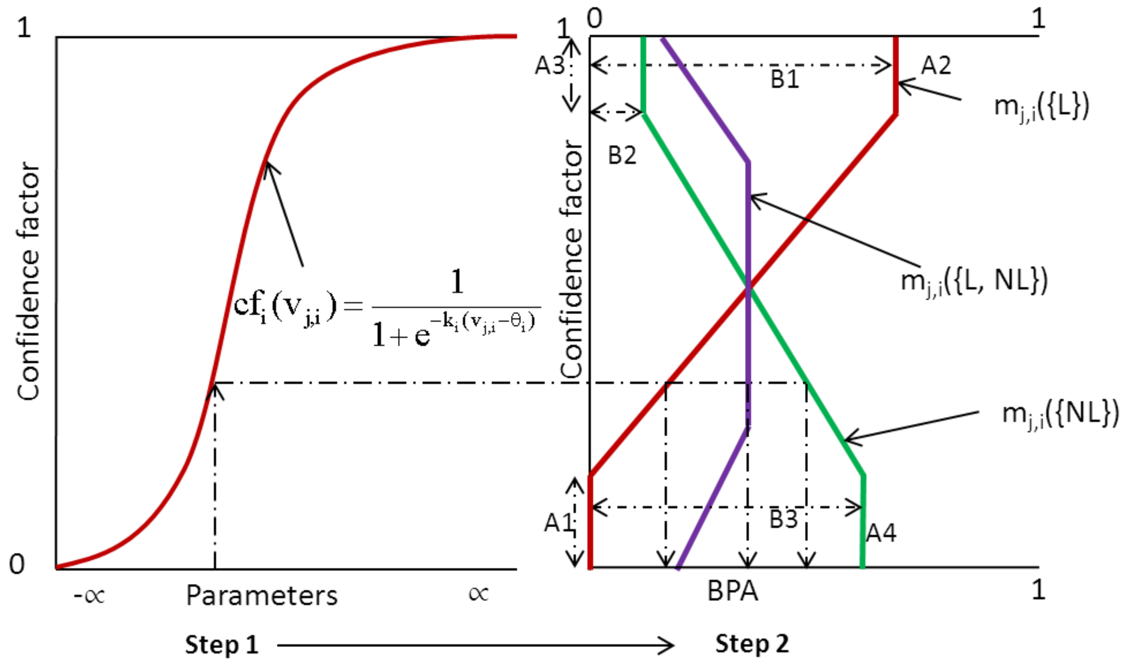



Figure 8.3: Transformation of data into BPAs (adapted from Beynon 2005)

After conversion of evidences into BPAs, combination rules have been applied to evaluate the joint evidences of different kinds of failures.

### 8.5.2 Rules of Combination

In D-S theory, the evidences from multiple sources are integrated using combination rules. The Dempster's rule of combination rule was originally used in D-S theory. However, various other combination rules have been developed by different investigators over the time. In addition to Dempster's rule, other combination rules include the Mixing or Averaging Rule, Yager's Modified Dempster's Rule, Inagaki's Unified Combination Rule, Zhang's Center Combination Rule, Dubois and Prade's Disjunctive Consensus Rule and so forth (Sentz and Ferson 2002). In this study, the Dempster's rule of combination has been used which combines two BPAs, $m_1$ and $m_2$ and estimates the joint BPA, $m_{1\text{-}2}$ emphasizing on the agreement of the sources of evidences and ignoring the conflicting evidence (Sentz and Ferson 2002). Equation 8.7 expresses the mathematical formula of Dempster's combination rule (Klir and Folger 1988):

$$m_{1-2}(A) = \frac{\sum_{B\cap C=A} m_1(B)m_2(C)}{1-K} \quad \text{when } A \neq \phi;$$

$$\text{and} \quad m_{1-2}(\phi) = 0 \qquad [8.7]$$

$$\text{where} \quad K = \sum_{B\cap C=\phi} m_1(B)m_2(C)$$

The term *K* represents the degree of conflict between two different sources B and C and 1-K is the normalization factors.

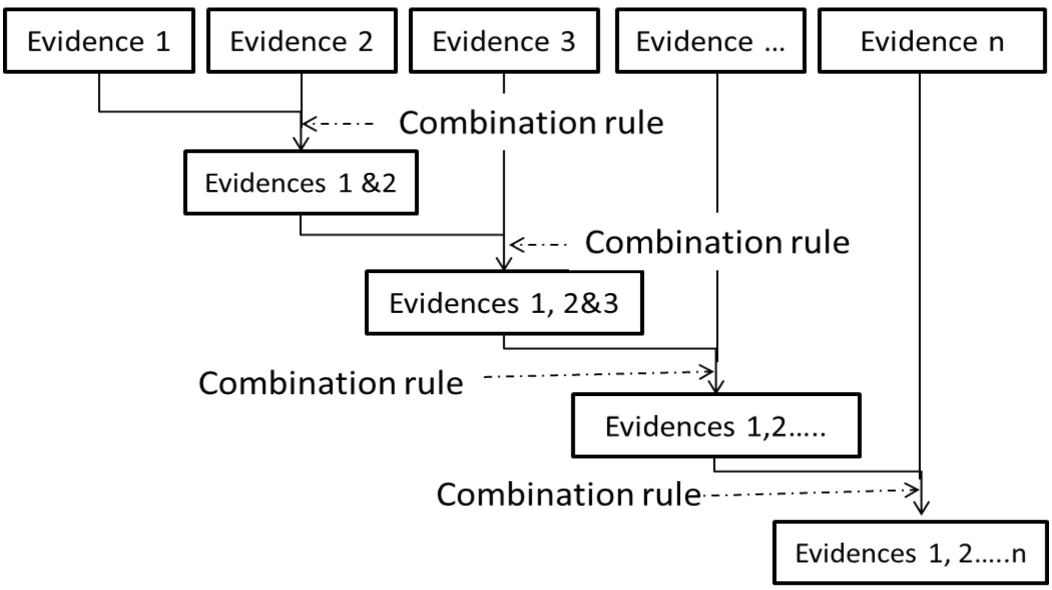



Figure 8.4: Cascade application of Dempster's rule

It is convenient to employ Dempster's combination rule between two evidences. However, evidences often come from more than two sources which are not possible to implement in a single rule at a time. For example, three sources of evidences exist in all phases of this integration. In this situation, Dempster's combination rule has been employed by cascading different evidences. Figure 8.4 shows the general cascade application of Dempster's combination rule between the multiple sources of evidences. Initially, Dempster's rule is applied between two evidences and joint BPAs ({L}, {NL}, {L, NL}) are evaluated which is considered as a single evidence. Hereafter, Dempster's rule is applied between combined single evidence and third evidence. The process continues until the last evidence is combined.

## 8.6 Implementation of Decision Support System

In different chapters of this thesis, the development of different models and their implementations have been described in details, however, fragmentally. This section describes a comprehensive proof-of-evidence of the developed integrated DSS under normal operating condition and under failure condition. The integration process has been demonstrated using the WDS described in Chapter 3.

### 8.6.1 Data Preparation

The implementation of the DSS depends on the model dependent secondary data and additional primary data as additional evidences. The model dependent secondary data include leakage potential, WQF potential, hydraulic utility, water quality utility and indices of leakage propensity in different nodes. The additional primary data include historical pipe bursts & water quality failures, recent consumer complaints, and water quality laboratory test reports. The historical water quality failures and recent water quality complaint parameters include the number of reported illness, color and turbidity, drop of free residual chlorine and odor and so forth (Table 6.8). Recent consumer complaints include pipe bursts and water quality complaints received from consumers. For the all recent complaints, distances from the source of complaints have been considered and recorded. In case of laboratory test report, the sample locations (i.e., distances) with respect to the nearest node / pipe also have been considered as recorded evidences. Since the leakage potential (Chapter 4) model and WQF potential (Chapter 6) model have been demonstrated using different WDSs than the network used in this chapter, a typical average values of leakage potential and the WQF potential have been used in all cases. The other parameters such as hydraulic utility & water quality utility and ILPs have been used as same as described earlier in Chapter 3 and Chapter 5. Table 8.2 shows the assumed number of pipe bursts and leakage potentials for different pipes and historical water quality failure events and WQF potentials in different nodes.`

Table 8.2: Primary data used in the integration phase

| Pipe/Node number | No. of pipe burst | Leakage potential | Historical quality failure (nodal) | Nodal WQF potentials |
|---|---|---|---|---|
| 1 | 0 | 0.34 | 0 | 0.27 |
| 2 | 0 | 0.41 | 0 | 0.38 |
| 3 | 1 | 0.37 | 0 | 0.31 |
| 4 | 0 | 0.33 | 0 | 0.30 |
| 5 | 0 | 0.45 | 1 | 0.44 |
| 6 | 0 | 0.35 | 0 | 0.28 |
| 7 | 0 | 0.42 | 0 | 0.37 |
| 8 | 1 | 0.33 | 2 | 0.26 |
| 9 | 0 | 0.48 | 0 | 0.42 |
| 10 | 0 | 0.42 | 0 | 0.33 |
| 11 | 0 | 0.34 | 1 | 0.32 |
| 12 | 1 | 0.36 | 2 | 0.35 |
| 13 | 0 | 0.49 | 5 | 0.49 |
| 14 | 0 | 0.49 | 2 | 0.39 |
| 15 | 0 | 0.41 | 1 | 0.39 |
| 16 | 0 | 0.38 | 0 | 0.34 |
| 17 | 0 | 0.32 | 0 | 0.26 |
| 18 | 0 | 0.38 | 0 | 0.36 |
| 19 | 1 | 0.31 | 1 | 0.24 |
| 20 | 0 | 0.31 | 0 | 0.30 |
| 21 | 1 | 0.36 | 0 | 0.32 |
| 22 | 0 | 0.31 | 0 | 0.21 |
| 23 | 0 | 0.38 | 0 | 0.32 |
| 24 | 0 | 0.45 | 2 | 0.37 |
| 25 | 3 | 0.49 | 0 | 0.44 |
| 26 | 0 | 0.48 | | |
| 27 | 0 | 0.47 | | |
| 28 | 0 | 0.48 | | |
| 29 | 2 | 0.48 | | |
| 30 | 0 | 0.49 | | |
| 31 | 0 | 0.31 | | |
| 32 | 1 | 0.40 | | |
| 33 | 0 | 0.37 | | |
| 34 | 3 | 0.48 | | |
| 35 | 0 | 0.43 | | |
| 36 | 0 | 0.36 | | |
| 37 | 4 | 0.40 | | |
| 38 | 0 | 0.50 | | |
| 39 | 3 | 0.50 | | |
| 40 | 1 | 0.40 | | |

The network failure condition has been simulated by disconnecting the failed pipe from the remaining network which has been modelled in EPANET by making pipe's initial status to 'close'. In this case, pipe 29 was modelled as a failed pipe. From Chapter 3, it was found that consumers can get full hydraulic utility from the WDS under the normal condition. However, in case of a failure (pipe 29), there is an issue of hydraulic disutility in some nodes. Due to the pipe 29 failure, the most critical duration of the day is 6-8 am and during this period, the WDS has highest demand multiplier of 1.49. The estimated hydraulic disutility at nodes 18, 22, 23, 24 and 25 during the period of 6-8 am are 0.976, 0.192, 1, 1 and 1, respectively. However, other nodes have full utilities during the day. It is noted that in spite of WDS failure, no violation of desired water quality utility was observed during the day. Under the normal operating condition, it is expected that the WDS will continue to operate without any hydraulic and quality consumer complaints or any positive laboratory test results. However, in failure condition, it is expected that utility company will receive different kinds of consumer complaints based on type of failures. In case of water quality events, the water company itself may find some quality issues in their regular laboratory test programs. To mimic the failure condition, consumer complaints are assumed in different locations of WDS over the time.

Table 8.3: Non-zero primary data under failure condition

| Time /Node No. | Reported cumulative consumer complaints | | | | | | | | | | | | Non-compliance lab. report | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Pipe bursts | | Illness | | | | Colors | | | | | | FRC | | | Turbidity | | | |
| | 20 | 21 | 12 | 13 | 19 | 24 | 12 | 13 | 15 | 17 | 19 | 25 | 13 | 26 | 27 | 11 | 13 | 17 | 21 |
| 0-2 | 0 | 1 | 2 | 2 | 1 | 3 | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 2-4 | 0 | 1 | 3 | 3 | 1 | 3 | 1 | 2 | 1 | 2 | 1 | 3 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 4-6 | 2 | 1 | 3 | 4 | 1 | 3 | 1 | 2 | 1 | 2 | 1 | 4 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 6-8 | 3 | 1 | 3 | 5 | 1 | 3 | 1 | 2 | 1 | 2 | 1 | 5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 8-10 | 4 | 1 | 3 | 6 | 1 | 3 | 1 | 2 | 1 | 2 | 1 | 5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 10-12 | 4 | 1 | 3 | 6 | 1 | 3 | 1 | 2 | 1 | 2 | 1 | 5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 12-14 | 4 | 1 | 3 | 6 | 1 | 3 | 1 | 3 | 1 | 2 | 1 | 5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 14-16 | 4 | 1 | 3 | 6 | 1 | 3 | 1 | 3 | 1 | 2 | 1 | 5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 16-18 | 4 | 1 | 3 | 6 | 1 | 3 | 1 | 3 | 1 | 2 | 1 | 5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 18-20 | 4 | 1 | 3 | 6 | 1 | 3 | 1 | 3 | 1 | 2 | 1 | 5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 20-22 | 4 | 1 | 3 | 6 | 1 | 3 | 1 | 3 | 1 | 2 | 1 | 5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 22-24 | 4 | 1 | 3 | 6 | 1 | 3 | 1 | 3 | 1 | 2 | 1 | 5 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

Table 8.3 shows non-zero primary data under hydraulic and water quality failure conditions as additional evidences. The values of these parameters at other nodes which are not provided in Table 8.3 are zeros. It is also noted that the distances from the complaint sources to the candidate nodes varies. For simplicity, all the distances have been considered as a single value of 0.3 km.

Table 8.4 shows a list of assumed controlling parameters used to convert different complaints to the relevant ESC and EIC. All of these parameters have been assumed based on the expert judgment. The values of these parameters can vary one expert to another expert; however, impact of the variations should not be significant to dilute the model results.

Table 8.4: Assumed constants to convert ESC & EIC

| Parameters | Coefficients | |
|---|---|---|
| | a | w |
| Pipe burst | 2 | - |
| Illness | 2 | 1 |
| Color | 2 | 0.5 |
| Drop of FRC | 2 | 0.6 |
| Turbidity | 2 | 0.7 |

### 8.6.2 Estimation of BPAs

After gathering relevant data, the BPAs are evaluated following the procedure described in section 8.5.1. Primary data are normalized using a sigmoid function as shown in Equation 8.3. The leakage potential, WQF potential, hydraulic and water quality utility are in a range of [0 1] and no further normalization is necessary.

Table 8.5: Controlling parameters for normalization and BPAs estimation

| Controlling Parameters | Normalization | | BPAs | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | k | $\theta$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ | $B_1$ | $B_2$ | $B_3$ |
| Leakage potential | - | - | 0.1 | 0.1 | 0.1 | 0.1 | 0.8 | 0.1 | 0.5 |
| Hydraulic utility | - | - | 0.1 | 0.1 | 0.1 | 0.1 | 0.8 | 0.1 | 0.5 |
| Historical pipe burst | 0.5 | 1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.8 | 0.1 | 0.5 |
| WQF potential | - | - | 0.2 | 0.1 | 0.1 | 0.1 | 0.8 | 0.1 | 0.5 |
| Water quality utility | - | - | 0.2 | 0.1 | 0.1 | 0.1 | 0.8 | 0.1 | 0.5 |
| Historical WQF | 0.1 | 2 | 0.2 | 0.1 | 0.1 | 0.1 | 0.8 | 0.1 | 0.5 |
| Hydraulic consumer complaints | 0.3 | 1.5 | 0.1 | 0.1 | 0.2 | 0.1 | 0.9 | 0.1 | 0.5 |
| Leakage propensity | 0.3 | 1.5 | 0.1 | 0.1 | 0.2 | 0.1 | 0.9 | 0.1 | 0.5 |
| Water quality consumer complaints | 0.9 | 2 | 0.0 | 0.1 | 0.1 | 0.1 | 1.0 | 0.1 | 0.4 |
| Laboratory results | 0.9 | 2 | 0.0 | 0.1 | 0.1 | 0.1 | 0.7 | 0.1 | 0.7 |

The normalization of different evidences is controlled by two parameters ( $k_i$ & $\theta_i$) whereas the BPAs are controlled by seven parameters ($A_1$, $A_2$, $A_3$, $A_4$, $B_1$, $B_2$, and $B_3$). For the evaluation of the state of different components of a WDS, the values of the controlling parameters require careful selection. Table 8.5 shows the controlling parameters used for the normalization and the

BPAs estimation in this demonstration. Using the normalized values of evidences, the BPAs are evaluated using Equations 8.4, 8.5, and 8.6. After the estimation of individual BPAs, the Dempster rule combination has been applied.

### 8.6.3 Results and Discussion

#### 8.6.3.1 Hydraulic Prognostic Investigation (H, P)

The hydraulic prognosis analysis is based on the performance measure of WDS in past, present and future conditions which are reflected in historical pipe bursts, hydraulic disutility, and leakage potential of different nodes, respectively. Based on these evidences, the state of WDS for a likely failure, not likely failure and ignorance (likely or not likely) of failure under normal operating condition as well as under failure condition have been estimated. Table 8.6 shows the hydraulic prognosis results of top four likely pipes (in order) under normal condition. The pipes with the most likely, the 2nd, the 3rd, and the 4th most likely chances of failure are no. 34, 39, 37, and 25, respectively. The values of {L} and {NL} are complementary. If a node has highest {L} value, it has lowest {NL} value among all the nodes. It is observed that the {L} values have proportional relation to the available pressure profile and inverse relation with the available water demand. The time period of 6-8 am has the highest demand multiplying factor (i.e., maximum demand) and, therefore, lowest available pressure. During this period the {L} is lowest and {NL} highest which indicates lower chances of failure. It is understandable that at low pressure, the chance of a pipe failure is minimal. However, in this model, this relationship is valid until the nodal hydraulic utilities are to a certain limit. In any case, hydraulic utility falls down from the desired level, the prognosis results shows the increase of chances for failures, in spite of pressure drop. This has been reflected from a similar solution under a failure condition.

Table 8.7 shows the hydraulic prognosis results of top four likely pipes (in order) under failure condition. This table also shows that under the failure condition, the prognosis results changed in a certain extent in all time steps. However, the changes in different pipes during the period of 6-8 am are drastic compared to the other time steps because of the extreme pressure drop which has reduced the hydraulic utility in a considerable extent.

Table 8.6: Hydraulic prognosis results of top four likely pipes (in order) under normal condition

| Time (hour) | First | | | | Second | | | | Third | | | | Fourth | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Pipe No. | {L} | {NL} | {L, NL} | Pipe No. | {L} | {NL} | {L, NL} | Pipe No. | {L} | {NL} | {L, NL} | Pipe No. | {L} | {NL} | {L, NL} |
| 0-2 | 34 | 0.50 | 0.43 | 0.06 | 39 | 0.46 | 0.48 | 0.07 | 37 | 0.44 | 0.49 | 0.07 | 25 | 0.39 | 0.53 | 0.08 |
| 2-4 | 34 | 0.50 | 0.44 | 0.06 | 39 | 0.45 | 0.48 | 0.07 | 37 | 0.44 | 0.49 | 0.07 | 25 | 0.39 | 0.53 | 0.08 |
| 4-6 | 34 | 0.45 | 0.48 | 0.07 | 39 | 0.39 | 0.53 | 0.08 | 37 | 0.39 | 0.54 | 0.08 | 25 | 0.35 | 0.57 | 0.08 |
| 6-8 | 34 | 0.34 | 0.57 | 0.08 | 37 | 0.29 | 0.63 | 0.09 | 25 | 0.28 | 0.63 | 0.09 | 39 | 0.28 | 0.63 | 0.09 |
| 8-10 | 34 | 0.39 | 0.54 | 0.08 | 37 | 0.33 | 0.59 | 0.08 | 39 | 0.33 | 0.59 | 0.08 | 25 | 0.31 | 0.60 | 0.09 |
| 10-12 | 34 | 0.40 | 0.53 | 0.08 | 37 | 0.34 | 0.58 | 0.08 | 39 | 0.34 | 0.58 | 0.08 | 25 | 0.32 | 0.60 | 0.09 |
| 12-14 | 34 | 0.43 | 0.50 | 0.07 | 39 | 0.38 | 0.55 | 0.08 | 37 | 0.37 | 0.55 | 0.08 | 25 | 0.34 | 0.57 | 0.08 |
| 14-16 | 34 | 0.45 | 0.48 | 0.07 | 39 | 0.40 | 0.53 | 0.08 | 37 | 0.39 | 0.53 | 0.08 | 25 | 0.36 | 0.56 | 0.08 |
| 16-18 | 34 | 0.41 | 0.52 | 0.07 | 37 | 0.35 | 0.57 | 0.08 | 39 | 0.35 | 0.57 | 0.08 | 25 | 0.33 | 0.59 | 0.08 |
| 18-20 | 34 | 0.40 | 0.52 | 0.07 | 37 | 0.34 | 0.57 | 0.08 | 39 | 0.34 | 0.57 | 0.08 | 25 | 0.32 | 0.59 | 0.08 |
| 20-22 | 34 | 0.42 | 0.51 | 0.07 | 39 | 0.36 | 0.56 | 0.08 | 37 | 0.36 | 0.56 | 0.08 | 25 | 0.33 | 0.58 | 0.08 |
| 22-24 | 34 | 0.45 | 0.49 | 0.07 | 39 | 0.39 | 0.53 | 0.08 | 37 | 0.39 | 0.54 | 0.08 | 25 | 0.35 | 0.57 | 0.08 |

Table 8.7: Hydraulic prognosis results of top four likely pipes in order under failure condition

| Time (hour) | First | | | | Second | | | | Third | | | | Fourth | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Pipe No. | {L} | {NL} | {L, NL} | Pipe No. | {L} | {NL} | {L, NL} | Pipe No. | {L} | {NL} | {L, NL} | Pipe No. | {L} | {NL} | {L, NL} |
| 0-2 | 34 | 0.53 | 0.42 | 0.06 | 25 | 0.43 | 0.50 | 0.07 | 29 | 0.43 | 0.50 | 0.07 | 39 | 0.42 | 0.51 | 0.07 |
| 2-4 | 34 | 0.52 | 0.42 | 0.06 | 25 | 0.43 | 0.50 | 0.07 | 29 | 0.43 | 0.50 | 0.07 | 39 | 0.42 | 0.51 | 0.07 |
| 4-6 | 34 | 0.47 | 0.47 | 0.07 | 25 | 0.39 | 0.53 | 0.08 | 29 | 0.39 | 0.54 | 0.08 | 39 | 0.36 | 0.56 | 0.08 |
| 6-8 | 34 | 0.86 | 0.12 | 0.02 | 39 | 0.79 | 0.18 | 0.03 | 40 | 0.71 | 0.25 | 0.04 | 25 | 0.56 | 0.39 | 0.06 |
| 8-10 | 34 | 0.41 | 0.52 | 0.07 | 25 | 0.35 | 0.57 | 0.08 | 29 | 0.34 | 0.58 | 0.08 | 39 | 0.29 | 0.62 | 0.09 |
| 10-12 | 34 | 0.42 | 0.51 | 0.07 | 25 | 0.36 | 0.56 | 0.08 | 29 | 0.35 | 0.57 | 0.08 | 39 | 0.30 | 0.61 | 0.09 |
| 12-14 | 34 | 0.45 | 0.48 | 0.07 | 25 | 0.38 | 0.54 | 0.08 | 29 | 0.38 | 0.55 | 0.08 | 39 | 0.34 | 0.58 | 0.08 |
| 14-16 | 34 | 0.47 | 0.46 | 0.07 | 25 | 0.40 | 0.53 | 0.08 | 29 | 0.39 | 0.53 | 0.08 | 39 | 0.36 | 0.56 | 0.08 |
| 16-18 | 34 | 0.43 | 0.50 | 0.07 | 25 | 0.36 | 0.56 | 0.08 | 29 | 0.36 | 0.56 | 0.08 | 39 | 0.31 | 0.60 | 0.09 |
| 18-20 | 34 | 0.43 | 0.50 | 0.07 | 25 | 0.36 | 0.56 | 0.08 | 29 | 0.35 | 0.56 | 0.08 | 39 | 0.31 | 0.60 | 0.09 |
| 20-22 | 34 | 0.44 | 0.49 | 0.07 | 25 | 0.37 | 0.55 | 0.08 | 29 | 0.36 | 0.56 | 0.08 | 39 | 0.32 | 0.59 | 0.08 |
| 22-24 | 34 | 0.47 | 0.47 | 0.07 | 25 | 0.39 | 0.53 | 0.08 | 29 | 0.39 | 0.54 | 0.08 | 39 | 0.35 | 0.56 | 0.08 |

Table 8.8: Hydraulic diagnosis results of top four likely nodes (in order) under normal condition

| Time (hour) | First | | | | Second | | | | Third | | | | Fourth | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} |
| 0-2 | 25 | 0.55 | 0.44 | 0.01 | 20 | 0.49 | 0.49 | 0.02 | 27 | 0.41 | 0.58 | 0.02 | 24 | 0.38 | 0.60 | 0.02 |
| 2-4 | 25 | 0.54 | 0.44 | 0.01 | 20 | 0.49 | 0.49 | 0.02 | 27 | 0.40 | 0.58 | 0.02 | 24 | 0.38 | 0.60 | 0.02 |
| 4-6 | 25 | 0.49 | 0.49 | 0.02 | 20 | 0.44 | 0.54 | 0.02 | 27 | 0.35 | 0.63 | 0.02 | 24 | 0.34 | 0.64 | 0.02 |
| 6-8 | 25 | 0.39 | 0.59 | 0.02 | 20 | 0.36 | 0.62 | 0.02 | 7 | 0.29 | 0.69 | 0.02 | 15 | 0.28 | 0.70 | 0.02 |
| 8-10 | 25 | 0.43 | 0.55 | 0.02 | 20 | 0.40 | 0.58 | 0.02 | 15 | 0.30 | 0.68 | 0.02 | 7 | 0.29 | 0.68 | 0.02 |
| 10-12 | 25 | 0.44 | 0.54 | 0.02 | 20 | 0.41 | 0.58 | 0.02 | 15 | 0.30 | 0.68 | 0.02 | 24 | 0.30 | 0.68 | 0.02 |
| 12-14 | 25 | 0.47 | 0.51 | 0.02 | 20 | 0.43 | 0.55 | 0.02 | 27 | 0.33 | 0.65 | 0.02 | 24 | 0.33 | 0.65 | 0.02 |
| 14-16 | 25 | 0.49 | 0.49 | 0.02 | 20 | 0.45 | 0.53 | 0.02 | 27 | 0.35 | 0.63 | 0.02 | 24 | 0.34 | 0.64 | 0.02 |
| 16-18 | 25 | 0.45 | 0.53 | 0.02 | 20 | 0.41 | 0.57 | 0.02 | 24 | 0.31 | 0.67 | 0.02 | 27 | 0.31 | 0.67 | 0.02 |
| 18-20 | 25 | 0.45 | 0.54 | 0.02 | 20 | 0.41 | 0.57 | 0.02 | 24 | 0.31 | 0.67 | 0.02 | 15 | 0.30 | 0.67 | 0.02 |
| 20-22 | 25 | 0.46 | 0.52 | 0.02 | 20 | 0.42 | 0.56 | 0.02 | 27 | 0.32 | 0.66 | 0.02 | 24 | 0.31 | 0.66 | 0.02 |
| 22-24 | 25 | 0.49 | 0.50 | 0.02 | 20 | 0.44 | 0.54 | 0.02 | 27 | 0.34 | 0.63 | 0.02 | 24 | 0.34 | 0.64 | 0.02 |

Table 8.9: Hydraulic prognosis results of top four likely nodes (in order) under failure condition

| Time (hour) | First | | | | Second | | | | Third | | | | Fourth | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} |
| 0-2 | 20 | 0.69 | 0.30 | 0.01 | 25 | 0.54 | 0.45 | 0.01 | 27 | 0.39 | 0.59 | 0.02 | 17 | 0.39 | 0.59 | 0.02 |
| 2-4 | 20 | 0.70 | 0.29 | 0.01 | 25 | 0.55 | 0.44 | 0.01 | 27 | 0.40 | 0.58 | 0.02 | 17 | 0.38 | 0.60 | 0.02 |
| 4-6 | 20 | 0.66 | 0.33 | 0.01 | 25 | 0.49 | 0.49 | 0.02 | 17 | 0.36 | 0.62 | 0.02 | 27 | 0.35 | 0.63 | 0.02 |
| 6-8 | 20 | 0.93 | 0.06 | 0.00 | 25 | 0.85 | 0.15 | 0.00 | 27 | 0.75 | 0.24 | 0.01 | 26 | 0.71 | 0.28 | 0.01 |
| 8-10 | 20 | 0.66 | 0.33 | 0.01 | 25 | 0.41 | 0.57 | 0.02 | 17 | 0.33 | 0.65 | 0.02 | 15 | 0.31 | 0.67 | 0.02 |
| 10-12 | 20 | 0.67 | 0.32 | 0.01 | 25 | 0.42 | 0.57 | 0.02 | 17 | 0.33 | 0.65 | 0.02 | 15 | 0.31 | 0.67 | 0.02 |
| 12-14 | 20 | 0.71 | 0.28 | 0.01 | 25 | 0.46 | 0.52 | 0.02 | 17 | 0.35 | 0.63 | 0.02 | 15 | 0.33 | 0.65 | 0.02 |
| 14-16 | 20 | 0.72 | 0.27 | 0.01 | 25 | 0.48 | 0.50 | 0.02 | 17 | 0.36 | 0.62 | 0.02 | 15 | 0.34 | 0.64 | 0.02 |
| 16-18 | 20 | 0.68 | 0.31 | 0.01 | 25 | 0.43 | 0.55 | 0.02 | 17 | 0.34 | 0.64 | 0.02 | 15 | 0.32 | 0.66 | 0.02 |
| 18-20 | 20 | 0.67 | 0.32 | 0.01 | 25 | 0.42 | 0.56 | 0.02 | 17 | 0.33 | 0.64 | 0.02 | 15 | 0.31 | 0.67 | 0.02 |
| 20-22 | 20 | 0.69 | 0.30 | 0.01 | 25 | 0.44 | 0.54 | 0.02 | 17 | 0.34 | 0.64 | 0.02 | 15 | 0.32 | 0.66 | 0.02 |
| 22-24 | 20 | 0.71 | 0.28 | 0.01 | 25 | 0.47 | 0.51 | 0.02 | 17 | 0.36 | 0.62 | 0.02 | 22 | 0.34 | 0.64 | 0.02 |

It is noted that the failure condition has been created by assigning a leakage demand at node 20. However, from the topology of the network and the top four most likely failure pipes, it is perceived that the identified leakage node is no. 25 which is not true. Hence, from the hydraulic prognosis results, it is not possible to identify the leaky node. However, an informed guess can be made about the presence of leakage in the system. If the network continues to run without any failure events, a daily prognosis results should not change significantly. To identify the failure location, a diagnostic investigation is necessary which have been discussed in later on in this chapter.

#### 8.6.3.2 Hydraulic Diagnostic Investigation (H, D)

Similar to the prognosis analysis, the diagnostic hydraulic analysis has been carried out. The hydraulic diagnostic analysis is based on the hydraulic prognosis analysis results / hydraulic state of WDS, consumers' complaints and estimated leakage propensities at different nodes. Based on these evidences, likely failure, not likely failure and ignorance (likely or not likely) of failure of particular condition have been estimated. Following the methodology described previously, Table 8.8 shows the hydraulic diagnosis results of the top four likely nodes (in order) under normal condition. From

Table 8.7 and Table 8.8, it is evident that, in the normal condition, both diagnostic and prognostic investigation identifies the same node as the most probable location of failure. As no significant changes in the BPAs ({L}, {NL}, {L, NL}) from normal operating BPAs are not observed, it does provide any indication of failure in the system. However, under the failure condition, from

Table 8.9, it is realized that the diagnostic investigation results have changed in a considerable extent indicating a probable failure in the system. Most importantly, it is perceived (Table 8.9) that the diagnostic investigation results have identified a different node (Node 20) as the most probable leaky node in the system which was the leaky node synthetically created by assigning an extra leakage demand.

#### 8.6.3.3 Water Quality Prognostic Investigation (Q, P)

Similar to the hydraulic prognosis and diagnosis analysis, water quality prognosis and diagnosis analysis have been carried out. Following the methodology described earlier, Table 8.10 shows the water quality prognosis results under normal condition. From Table 8.10, it is seen that the chances of water quality failure during the first few hours are extremely high. This is because, the water quality utility during the first couple of hours are very low due to low residual chlorine concentration in different nodes. This lower residual chlorine concentration was due to travel time of source residual chlorine (a simulation issue). However, in reality, this does not happen as the WDS supplies water after enough water flushing and if the network is simulated for an existing operating condition, initial residual chlorine concentration will show up from the beginning of the simulation. Therefore, it is required to avoid couple of hour simulation results. Actual results will show up after these periods which have been reflected in Table 8.10. From Table 8.10, it is found that the pipe 15 has highest chances of water quality failure. It is noted that, as described in Chapter 3, due to the hydraulic failure at a node, no impact on water quality failures were observed because the hydraulic changes did not impact the water quality failure in the distribution system in this case. However, to check the sensitivity of the water quality prognosis model, a minor change was incorporated (5% increase) of water quality failure potential under normal condition. From that case, changes are also observed in the chances of water quality failure. However, the changes were not enough to change the ranking of nodes for the chances of failure. Table 8.11 shows the water quality prognosis results of the top four likely nodes (in order) under minor changes in WQF potentials.

#### 8.6.3.4 Water Quality Diagnostic Investigation (Q, D)

Similar to the water quality prognosis analysis, the water quality diagnostic analysis has been carried out. The diagnostic analysis is based on the quality prognosis analysis results / water quality state of WDS, consumers' complaints and routine / special laboratory test results. Based on these evidences, likely failure, not likely failure and ignorance (likely or not likely) of failure of particular condition have been estimated. Following the methodology described previously, Table 8.12 shows the water quality diagnosis results of the top four likely nodes (in order) under normal condition. From Table 8.10, Table 8.11and Table 8.12, it is patent that in the normal condition, both diagnostic and prognostic investigations nodes identify the same node as a most probable failure location. As no significant changes in the BPAs ({L}, {NL}, {L, NL}) from normal condition are observed, it does not provide indication of failure in the system. However, under the failure condition, from Table 8.13, it is evident that the diagnostic investigation results have changed in considerable extents indicating a probable failure in the system. Most importantly, it is seen (Table 8.13) that the diagnostic investigation results identify the different node (Node 13) as the most probable location of water quality failure in the system which is consistent with the received consumer complaints and laboratory test results.

Table 8.10: Water quality prognosis results of top four likely nodes (in order) under normal condition

| Time (hour) | First | | | | Second | | | | Third | | | | Fourth | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} |
| 0-2 | 27 | 0.81 | 0.16 | 0.03 | 26 | 0.79 | 0.18 | 0.03 | 25 | 0.76 | 0.20 | 0.04 | 20 | 0.67 | 0.28 | 0.05 |
| 2-4 | 27 | 0.32 | 0.57 | 0.11 | 15 | 0.27 | 0.62 | 0.11 | 11 | 0.26 | 0.63 | 0.11 | 16 | 0.25 | 0.64 | 0.11 |
| 4-6 | 15 | 0.27 | 0.62 | 0.11 | 11 | 0.26 | 0.63 | 0.11 | 27 | 0.26 | 0.63 | 0.11 | 16 | 0.25 | 0.64 | 0.11 |
| 6-8 | 15 | 0.27 | 0.62 | 0.11 | 11 | 0.26 | 0.63 | 0.11 | 27 | 0.26 | 0.63 | 0.11 | 16 | 0.25 | 0.64 | 0.11 |
| 8-10 | 15 | 0.27 | 0.62 | 0.11 | 11 | 0.26 | 0.63 | 0.11 | 27 | 0.26 | 0.63 | 0.11 | 16 | 0.25 | 0.64 | 0.11 |
| 10-12 | 15 | 0.27 | 0.62 | 0.11 | 11 | 0.26 | 0.63 | 0.11 | 27 | 0.26 | 0.63 | 0.11 | 16 | 0.25 | 0.64 | 0.11 |
| 12-14 | 15 | 0.27 | 0.62 | 0.11 | 11 | 0.26 | 0.63 | 0.11 | 27 | 0.26 | 0.63 | 0.11 | 16 | 0.25 | 0.64 | 0.11 |
| 14-16 | 15 | 0.27 | 0.62 | 0.11 | 11 | 0.26 | 0.63 | 0.11 | 27 | 0.26 | 0.63 | 0.11 | 16 | 0.25 | 0.64 | 0.11 |
| 16-18 | 15 | 0.27 | 0.62 | 0.11 | 11 | 0.26 | 0.63 | 0.11 | 27 | 0.26 | 0.63 | 0.11 | 16 | 0.25 | 0.64 | 0.11 |
| 18-20 | 15 | 0.27 | 0.62 | 0.11 | 11 | 0.26 | 0.63 | 0.11 | 27 | 0.26 | 0.63 | 0.11 | 16 | 0.25 | 0.64 | 0.11 |
| 20-22 | 15 | 0.27 | 0.62 | 0.11 | 11 | 0.26 | 0.63 | 0.11 | 27 | 0.26 | 0.63 | 0.11 | 16 | 0.25 | 0.64 | 0.11 |
| 22-24 | 15 | 0.27 | 0.62 | 0.11 | 11 | 0.26 | 0.63 | 0.11 | 27 | 0.26 | 0.63 | 0.11 | 16 | 0.25 | 0.64 | 0.11 |

Table 8.11: Water quality prognosis results of top four likely nodes (in order) under minor changes in WQF potentials

| Time (hour) | First | | | | Second | | | | Third | | | | Fourth | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} |
| 0-2 | 27 | 0.82 | 0.15 | 0.03 | 26 | 0.80 | 0.17 | 0.03 | 25 | 0.77 | 0.19 | 0.03 | 20 | 0.68 | 0.27 | 0.05 |
| 2-4 | 27 | 0.34 | 0.55 | 0.11 | 15 | 0.29 | 0.61 | 0.11 | 11 | 0.27 | 0.62 | 0.11 | 16 | 0.27 | 0.62 | 0.11 |
| 4-6 | 15 | 0.29 | 0.61 | 0.11 | 11 | 0.27 | 0.62 | 0.11 | 27 | 0.27 | 0.62 | 0.11 | 16 | 0.27 | 0.62 | 0.11 |
| 6-8 | 15 | 0.29 | 0.61 | 0.11 | 11 | 0.27 | 0.62 | 0.11 | 27 | 0.27 | 0.62 | 0.11 | 16 | 0.27 | 0.62 | 0.11 |
| 8-10 | 15 | 0.29 | 0.61 | 0.11 | 11 | 0.27 | 0.62 | 0.11 | 27 | 0.27 | 0.62 | 0.11 | 16 | 0.27 | 0.62 | 0.11 |
| 10-12 | 15 | 0.29 | 0.61 | 0.11 | 11 | 0.27 | 0.62 | 0.11 | 27 | 0.27 | 0.62 | 0.11 | 16 | 0.27 | 0.62 | 0.11 |
| 12-14 | 15 | 0.29 | 0.61 | 0.11 | 11 | 0.27 | 0.62 | 0.11 | 27 | 0.27 | 0.62 | 0.11 | 16 | 0.27 | 0.62 | 0.11 |
| 14-16 | 15 | 0.29 | 0.61 | 0.11 | 11 | 0.27 | 0.62 | 0.11 | 27 | 0.27 | 0.62 | 0.11 | 16 | 0.27 | 0.62 | 0.11 |
| 16-18 | 15 | 0.29 | 0.61 | 0.11 | 11 | 0.27 | 0.62 | 0.11 | 27 | 0.27 | 0.62 | 0.11 | 16 | 0.27 | 0.62 | 0.11 |
| 18-20 | 15 | 0.29 | 0.61 | 0.11 | 11 | 0.27 | 0.62 | 0.11 | 27 | 0.27 | 0.62 | 0.11 | 16 | 0.27 | 0.62 | 0.11 |
| 20-22 | 15 | 0.29 | 0.61 | 0.11 | 11 | 0.27 | 0.62 | 0.11 | 27 | 0.27 | 0.62 | 0.11 | 16 | 0.27 | 0.62 | 0.11 |
| 22-24 | 15 | 0.29 | 0.61 | 0.11 | 11 | 0.27 | 0.62 | 0.11 | 27 | 0.27 | 0.62 | 0.11 | 16 | 0.27 | 0.62 | 0.11 |

Table 8.12: Water quality diagnosis results of top four likely nodes (in order) under normal condition

| Time (hour) | First | | | | Second | | | | Third | | | | Fourth | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} |
| 0-2 | 27 | 0.86 | 0.14 | 0.00 | 26 | 0.85 | 0.15 | 0.00 | 25 | 0.83 | 0.17 | 0.00 | 20 | 0.75 | 0.24 | 0.01 |
| 2-4 | 27 | 0.46 | 0.52 | 0.01 | 15 | 0.41 | 0.57 | 0.01 | 11 | 0.40 | 0.58 | 0.01 | 16 | 0.40 | 0.59 | 0.01 |
| 4-6 | 15 | 0.41 | 0.57 | 0.01 | 11 | 0.40 | 0.58 | 0.01 | 27 | 0.40 | 0.59 | 0.01 | 16 | 0.40 | 0.59 | 0.01 |
| 6-8 | 15 | 0.41 | 0.57 | 0.01 | 11 | 0.40 | 0.58 | 0.01 | 27 | 0.40 | 0.59 | 0.01 | 16 | 0.40 | 0.59 | 0.01 |
| 8-10 | 15 | 0.41 | 0.57 | 0.01 | 11 | 0.40 | 0.58 | 0.01 | 27 | 0.40 | 0.59 | 0.01 | 16 | 0.40 | 0.59 | 0.01 |
| 10-12 | 15 | 0.41 | 0.57 | 0.01 | 11 | 0.40 | 0.58 | 0.01 | 27 | 0.40 | 0.59 | 0.01 | 16 | 0.40 | 0.59 | 0.01 |
| 12-14 | 15 | 0.41 | 0.57 | 0.01 | 11 | 0.40 | 0.58 | 0.01 | 27 | 0.40 | 0.59 | 0.01 | 16 | 0.40 | 0.59 | 0.01 |
| 14-16 | 15 | 0.41 | 0.57 | 0.01 | 11 | 0.40 | 0.58 | 0.01 | 27 | 0.40 | 0.59 | 0.01 | 16 | 0.40 | 0.59 | 0.01 |
| 16-18 | 15 | 0.41 | 0.57 | 0.01 | 11 | 0.40 | 0.58 | 0.01 | 27 | 0.40 | 0.59 | 0.01 | 16 | 0.40 | 0.59 | 0.01 |
| 18-20 | 15 | 0.41 | 0.57 | 0.01 | 11 | 0.40 | 0.58 | 0.01 | 27 | 0.40 | 0.59 | 0.01 | 16 | 0.40 | 0.59 | 0.01 |
| 20-22 | 15 | 0.41 | 0.57 | 0.01 | 11 | 0.40 | 0.58 | 0.01 | 27 | 0.40 | 0.59 | 0.01 | 16 | 0.40 | 0.59 | 0.01 |
| 22-24 | 15 | 0.41 | 0.57 | 0.01 | 11 | 0.40 | 0.58 | 0.01 | 27 | 0.40 | 0.59 | 0.01 | 16 | 0.40 | 0.59 | 0.01 |

Table 8.13: Water quality diagnosis results of top four likely nodes (in order) under failure condition

| Time (hour) | First | | | | Second | | | | Third | | | | Fourth | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} | Node No. | {L} | {NL} | {L, NL} |
| 0-2 | 27 | 0.87 | 0.13 | 0.00 | 26 | 0.86 | 0.14 | 0.00 | 25 | 0.83 | 0.16 | 0.00 | 24 | 0.80 | 0.19 | 0.00 |
| 2-4 | 27 | 0.49 | 0.50 | 0.01 | 13 | 0.46 | 0.53 | 0.01 | 12 | 0.45 | 0.54 | 0.01 | 15 | 0.43 | 0.55 | 0.01 |
| 4-6 | 13 | 0.48 | 0.51 | 0.01 | 12 | 0.45 | 0.54 | 0.01 | 15 | 0.43 | 0.55 | 0.01 | 27 | 0.42 | 0.56 | 0.01 |
| 6-8 | 13 | 0.50 | 0.49 | 0.01 | 12 | 0.45 | 0.54 | 0.01 | 15 | 0.43 | 0.55 | 0.01 | 27 | 0.42 | 0.56 | 0.01 |
| 8-10 | 13 | 0.52 | 0.47 | 0.01 | 12 | 0.45 | 0.54 | 0.01 | 15 | 0.43 | 0.55 | 0.01 | 27 | 0.42 | 0.56 | 0.01 |
| 10-12 | 13 | 0.52 | 0.47 | 0.01 | 12 | 0.45 | 0.54 | 0.01 | 15 | 0.43 | 0.55 | 0.01 | 27 | 0.42 | 0.56 | 0.01 |
| 12-14 | 13 | 0.52 | 0.47 | 0.01 | 12 | 0.45 | 0.54 | 0.01 | 15 | 0.43 | 0.55 | 0.01 | 27 | 0.42 | 0.56 | 0.01 |
| 14-16 | 13 | 0.52 | 0.47 | 0.01 | 12 | 0.45 | 0.54 | 0.01 | 15 | 0.43 | 0.55 | 0.01 | 27 | 0.42 | 0.56 | 0.01 |
| 16-18 | 13 | 0.52 | 0.47 | 0.01 | 12 | 0.45 | 0.54 | 0.01 | 15 | 0.43 | 0.55 | 0.01 | 27 | 0.42 | 0.56 | 0.01 |
| 18-20 | 13 | 0.52 | 0.47 | 0.01 | 12 | 0.45 | 0.54 | 0.01 | 15 | 0.43 | 0.55 | 0.01 | 27 | 0.42 | 0.56 | 0.01 |
| 20-22 | 13 | 0.52 | 0.47 | 0.01 | 12 | 0.45 | 0.54 | 0.01 | 15 | 0.43 | 0.55 | 0.01 | 27 | 0.42 | 0.56 | 0.01 |
| 22-24 | 13 | 0.52 | 0.47 | 0.01 | 12 | 0.45 | 0.54 | 0.01 | 15 | 0.43 | 0.55 | 0.01 | 27 | 0.42 | 0.56 | 0.01 |

## 8.7 Summary

In this chapter, developed models have been integrated under the framework of Dempster- Shafer theory of evidences which makes the whole project as a complete DSS. The developed DSS has capacities for diagnostic and prognostic investigation of water distribution failure by communicating different models and their inputs and outputs. It can estimate the likeliness, not likeliness and complete ignorance (likely, not likely) of different kinds of failure in the distribution system. The developed model has been applied to a WDS. To implement the DSS, secondary data estimated using different developed models described in different chapters of this thesis and addition primary data have been generated. From the demonstration, it is evident that the DSS has capabilities for integrated prognosis and diagnosis investigation of a WDS failure. Although the developed DSS has been implemented to relatively small WDS for the proof of concept, the developed DSS can be used for any WDS by modifying appropriate factors/parameters.

# CHAPTER 9 CONCLUSIONS AND RECOMMENDATIONS

## 9.1 Conclusions

The main objective of this research was to develop diagnostic and prognostic analysis techniques for WDS failures. To achieve this objective an integrated decision support system framework has been developed. The interventions based on the prognostic analysis will reduce the likelihood of failures, and in case of a failure, the diagnostic analysis will minimize the consequences of the failure. The prognostic capability of the framework increases the confidence in predictive analysis which helps to reduce likelihood of failure. The diagnostic capabilities of the framework reduce false positive and false negative prediction, and identify the failure location with minimal time after the occurrence which minimizes the consequences of failure. The outcomes of this research broadly addressed the uncertainties associated with WDS which improves the efficiency and effectiveness of diagnosis and prognosis analyses. The framework brings the modelling information, consumer complaints and laboratory test information under a single platform. The research also provides new insights on how to incorporate fuzzy set in the assessment of WDS failures.

The foundation stones of the developed framework are five 'novel' models which interact and complement each other under the framework. Among the five models three of them are prognosis model and two of them are diagnosis model. The first model is the reliability assessment model which addressed some of the missing components of the traditional reliability assessment. This model evaluates reliability and provides a measure of uncertainty in the estimated reliability which ultimately helps to design a more reliable WDS. For the first time, this model provides an option to the designer to select the level of uncertainties in the network reliability. In addition, the developed methodology is generic and can be easily implemented in similar types of infrastructures including oil & gas network, telecommunication network and so forth. An article based on this model has been submitted for publication in *ASCE Journal of Water Resource Planning and Management*.

The developed second model introduces the concept of "leakage potential" and develops a methodology to evaluate leakage potential in a WDS or a component of WDS. The model shows a unique way to evaluate the impacts of different influencing factors in leakage. The model brings the pressure dependent background leakage under a risk based methodology which has not been seen in the literature. From model implementation results, it reveals that among different influencing factors, some of the factors have more influence than others. It is identified that in a certain range, the operating system pressure and age of the network are the most important factors contributing to LP. For example, for the existing network condition in Bangkok, the network LP is not very sensitive to low operating pressure (17.9 psi). However, when pressure exceeds 30 m (42.9 psi), the network LP is more sensitive to the operating system pressure. The impact of age to LP is very gradual for the current operating system pressure of 12.56 m (17.9 psi). However, if the operating pressure, for example, increases to 45 m (64.3 psi), the LP will increase more noticeably for same age and other parameters combination. For higher operating pressure, LP is more sensitive in the age range of 30 - 60 years. An article based on this model has been published in the IWA Journal of Water Supply: Research and Technology – AQUA [61(4):240–252].

The developed third model identifies the presence of leakage, in case of a leakage; it can detect the position of a leakage in the nearest node / pipe of the WDS. To develop this model, fuzzy set has been used beyond its traditional application. The developed model is so efficient that it can identify a small hydraulic change in the WDS. In addition, this methodology introduces a new concept of 'indices of leakage propensity' which provide a measure of severity of the leakage in a WDS. An article based on this model has been published in *Urban Water Journal* [8 (6), 351–365].

The fourth model evaluates the WQF potential in WDS. The developed model identifies 17 *"causes"* against nine *"symptoms"* of water quality failure. This model has the capabilities to make "causes" and "symptoms" relationship which helps to evaluate WQF potential and relative importance of different water quality parameters. From the sensitivity analysis, it is found that the pipe age and material are the most sensitive parameters next to the coliform. The pH is the least sensitive "*cause"* of WQF. An article based on this model has been submitted for publication in the *Water Resource Management*.

The fifth model is extended from the WQF potential. The developed model identifies presence of any water quality event based on the sensory information using the WQF potential model. After detecting the presence of WQF event, the model source tracks the most probable origin of the detected contaminant. Finally, the model identifies the most vulnerable area resulting from WQF and identifies the most probable reason.

All the efforts made to develop different diagnostic and prognostic models are merged into the integrated decision support system which combines different models, their inputs and output from the developed models. It has the capacities for diagnostic and prognostic investigation of water distribution failure and can estimates the likeliness, not likeliness and complete ignorance (likely, not likely) of failures in the distribution system.

## 9.2 Limitations and Recommendations

In spite of significant efforts to reduce WDS failure, a large number of failure events, both SHF and WQF, occur every year. The main reason of these failures is the difficulties of understanding of spatially distributed WDS and its different uncertain parameters. In this research, an effort has been made for a better understanding and for a better modelling of WDS and its uncertain parameters. Due to the scale of the problem, this research has been conducted under certain limitations and assumptions. Following sections discussed different limitations of the research and related recommendation for further studies. The main recommendation for conducting research in this area goes further for better understanding and modelling of WDS uncertain parameters.

### 9.2.1 Proposed Framework

- Concentrating on the main objective of this research, the framework developed in this research does not consider the consequences of failures. To avoid lumping of the failure likelihood with consequences, the consequences of failures have been intentionally avoided. However, the consequence is a very important part to prioritize rehabilitation strategies. Therefore, the developed framework can be extended by incorporating consequences component of risk which will increase the capacity of the proposed framework.
- For different models, it assumed that sensor data are reasonably correct and uncertainties associated with sensor data have not been considered. Incorporation of sensor data uncertainties in different models will be interesting study.

- The diagnostic capabilities of the proposed framework are depended on calibrated hydraulic and water quality model. Further studies on model calibration and their influences on the integrated framework will be interesting to study.
- All the developed models have been developed under the framework of fuzzy set theory and integration of different models have been conducted under the Dempster- Shafer theory of evidences. However, the performances of the models and their integration under other frameworks might be an interesting idea.
- Due to data limitations, the different models of the developed framework have been implemented in different WDSs. The full implementation of the proposed framework to a single real WDS will be interesting.
- Different components of the proposed framework have been developed fragmentally and each model is a standalone application. However, an integrated DSS has been developed using the previously developed model results. It will be very interesting to develop software with all the capabilities described in this thesis. A conceptual integration of developed models with remote telemetry units (RTU), communication system, and database management system and field support system has been provided in 9.2.3 in this chapter later. Materialization of such software application will be pleasing to me.

### 9.2.2 Developed Models

All the models developed can be easily integrated with GIS or USEPA developed EPANET water distribution system modelling. Such integration will help users to use the developed models. To integrate with commercially available software, further modification is necessary.

Specific recommendations include:

- In the reliability assessment model, uncertainties have been considered for four parameters. Further consideration of other uncertain parameters is recommended.
- In the reliability assessment model, the main focus was related to the reliability of WSS. However, integration of reliability, robustness and resilience (Zhang et al. 2012) of a WSS will be a very interesting idea.
- Developed models deal with a large number of parameters and require intense computational efforts. Specially, reliability assessment and leakage location detection models are highly computation intensive. A faster computational power using multicore computer or network computers grid can reduce the computational time.

- In the leakage potential model, effects of different influential factors have been model based on a single decision maker approach. Inclusion of other decision maker's attitude might increase the confidence of the models. In addition, data on the effects of different influential factors are very limited. Collection of additional information on different influential factors will increase confidence in the model.
- In the WQF potential model, three decision makers participated in the evaluation process. However, the inclusion of additional decision makers' inputs might increase the model reliability.
- Further investigation of WQF detection in case of growth of contaminants in the WDS is also recommended.
- Like almost all of the risk-based modelling approaches, it is difficult to validate different models developed. Further study on the validation of different models will increase the confidence of different models.
- To demonstrate the integration of the proposed framework, pipe burst, water quality failure, laboratory test results are synthetically generated. Implementation of the developed models with real world problems is also recommended.
- To identify the optimum number of sensors for leakage and WQF detection and location, further studies on sensors optimization and placement are recommended.
- To compare the model performance, all the results can be calculated using a pressure-dependent simulation algorithm.

### 9.2.3 Decision Support System

The findings of this research are worth to create an independent software tool as a decision support system. The development of independent standalone commercial software was out of scope of this research. However, a conceptual architecture for a commercial package development has been provided. Figure 9.1 shows the conceptual architecture for a potential DSS based on this thesis. The proposed architecture has six components, namely, field installation system, communication, database management system, central processing unit, and decision and field support. A field installation system consists of remote terminal units (RTU) and different kinds of sensors such as pressure sensors, water quality sensors. A RTU is a microprocessor-controlled electronic device that will interface with the different kinds of sensors and central monitoring system through a communication system[23]. The collected data are managed and used in a database management system which will be used for computation, visualization and interpretation of results. Different kinds of data management systems include GIS system, CIS system, water quality and data models and a computational repository for temporary data storage during the computation process through the central processing units. All of the collected, transported and stored data will feed the central processing unit (CPU) of the DSS. The CPU is the main component of this thesis which has been described in different chapters of this thesis. The integration of different components of the CPU has been described in Chapter 8.

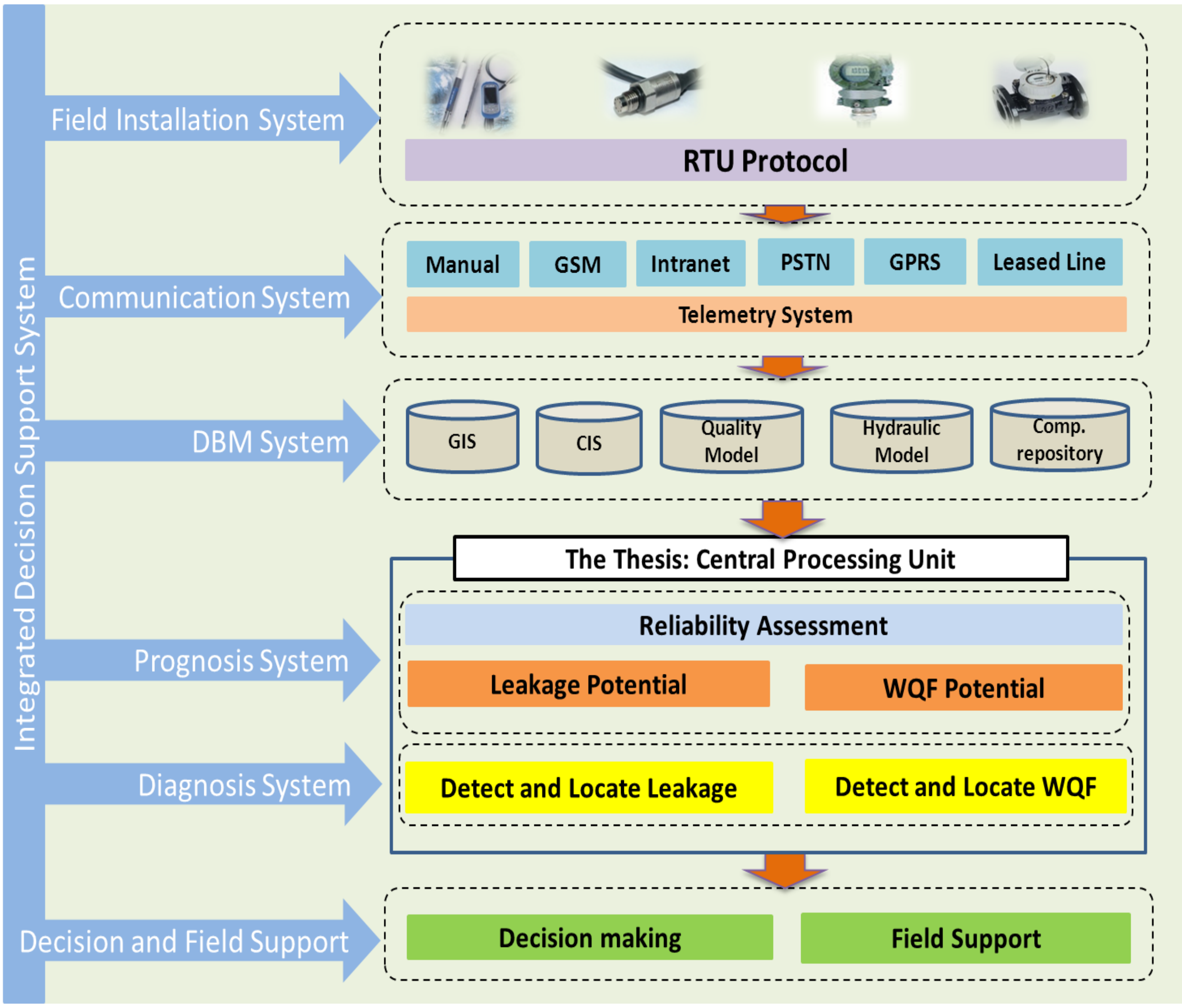



Figure 9.1: Conceptual architecture of proposed DSS

[23] A communication system can be manual data transportation, or different kind of telecommunication system such as GSM (Global System for Mobile Communications) network, GPRS (General packet radio service) wireless system, PSTN (public switched telephone network) telephone line or any other communication system.

Finally, based on the DSS results, the user will take informed decisions and take necessary action in the field. All the stage described in the commercial architecture can be easily materialized with necessary but existing expertise. In addition to the different components described in the architecture, existing knowledge to estimate volume of water lost, financial loss due to water quality failure can be investigated.

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